TOM: Topology Oriented Maintenance in Sparse Wireless Sensor Networks

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Abstract—**The physical number of sensor nodes constitutes a major cost factor for Wireless Sensor Networks (WSN) deployments. Hence, a natural goal is to minimize the number of sensor nodes to be deployed, while still maintaining the desired properties of the WSN. However, sparse networks even while connected, usually suffer from topology irregularities that negatively impact the network lifetime and responsiveness, i.e., sensor data delivery reliability and latency. In addition, sensor node failures easily complicate/enforce/aggravate these irregularities. Valuable efforts have been conducted to discover topology specific anomalies such as coverage holes or critical/bottleneck nodes. Unfortunately, these efforts suffer from at least one of the following drawbacks: (a) They are centralized and consequently inefficient in large-scale networks, (b) they are tailored to one class of anomalies, or (c) do not propose how to remedy the identified anomaly. In this paper, we focus on sparse WSN which usually show varied topology irregularities and propose an in-network and localized strategy that efficiently (i) discovers generic topology irregularities, and (ii) identifies locations for minimal number of new augmented sensor deployments to remedy topology irregularities and sustain the desired operational requirements. We show the effectiveness and efficiency of the solution through a set of extensive simulations.**

I. Introduction

Wireless Sensor Networks (WSN) constitute composite communication and computational systems. A typical WSN consists of multiple battery powered autonomous devices equipped with processing units for sensing target environmental attributes and communicating wirelessly. These characteristics allow high flexibility for deployment. While the simple construction of sensor nodes reduces their unit cost, this is counterweighted by the fact that a typical deployment requires multiple sensor nodes to provide communication coverage or effective monitoring. It is especially evident for uncontrolled deployments [1], where the network has to be over-supplied with sensor nodes to assure connectivity (despite power depletion, connectivity losses and failures, etc). This rapidly increases the WSN deployment costs. Hence, a natural trend is to target the deployment of sparse networks while preserving the deployment flexibility. A related incentive to limit the density of the deployed sensor nodes are network capacity benefits [2] from reduced congestion, interference and collisions. Unfortunately, a sparse deployment also comes with consequences. Although the network may be connected,

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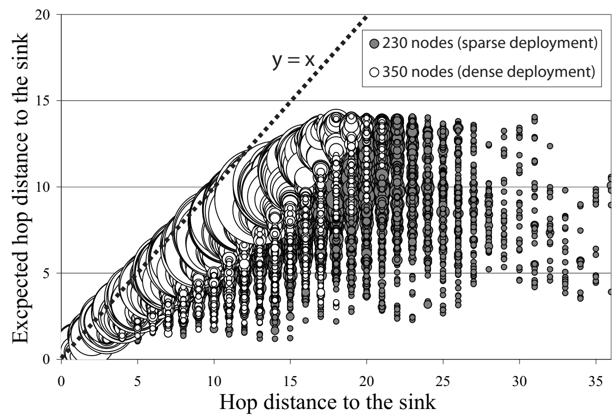

Fig. 1. Distribution of actual hop distances compared to expected distances.

even the optimal spanning tree over such sparse network often results in a highly irregular topology.

Through the discrepancy between Euclidean induced distance [5], [6] and the topology induced hop distance to the sink we can determine the existence of topological holes, critical [3] / bottleneck [4] nodes, and the non-uniform deployment of sensor nodes. This discrepancy arises only when there exists no *straight* route between the affected sensor node and the sink. Lengthy routes translate in higher latencies and higher/unbalanced energy consumption among the sensor nodes. As a result the WSN can suffer from unbalanced energy usage even under optimal energy conservation schemas, which usually leads to potential premature disconnections and partitioning. In addition, there exists a related major source of topology irregularities, namely the network failures. Sensor nodes often fail as they operate with finite energy capacities and in harsh environments. Usually in sparse networks, node failures directly impact the topology irregularities and negatively influence the network lifetime and responsiveness.

To show the severity of topology irregularities, we illustrate in Fig. 1 the distribution of the expected hop distance (deduced from the Euclidean distance of sensor nodes to the sink - Y axis) as a function of actual hop distance (derived from the shortest path routing tree - X axis). The size of the circles corresponds to the number of sensor nodes having the same characteristics and illustrates the occurrence frequency. The distribution was obtained from 1000 random topologies generated for deployments of 230 (sparse WSN) and 350 (dense WSN) sensor nodes over the same area (exact simulation settings are detailed in Section VI). For each sensor node, in the optimal scenario, the topology induced hop distance should be equal to the Euclidean induced hop distance and consequently all points should lie on the $y = x$ line. The case of dense network deployments shows that the topology generally follows a uniform distribution. Only a few sensor nodes have topology induced hop distances substantially different from the excepted Euclidean induced hop distances. This property is much desired for high responsiveness, optimized load balancing and hence prolonged lifetime. In case of a sparse deployment, the topology induced hop distance can substantially differ from the optimum, with great concentration of circles below the indicated $y = x$ line. Also the topology induced distances significantly exceed the maximal hop distance for the dense network scenario (15 hops). A topology, where the correlation between topology and Euclidean induced hop distances is low, is termed as an *irregular topology*. The observed irregularities in sparse deployments need to be alleviated using an efficient and comprehensive maintenance.

Most maintenance strategies often overlook this aspect of the topology (ir)regularity. The overextended routing paths, critical and bottleneck nodes, and unbalanced energy usage are all symptoms of an underlying irregular topology. The typical maintenance solutions concentrate on detecting and partially remedying a subset of these symptoms, e.g., restoring connectivity or coverage while neglecting the actual source of root causes. Therefore, it is desirable to avoid such irregularity induced problems by developing efficient techniques to maintain a regular topology. As the network regularity requirements are mostly application specific, the maintenance strategy should offer tunability in setting bounds on the extent of irregularities to tolerate. In order to provide efficient and contextualized maintenance and decentralized solutions, the techniques should utilize local information. In particular, our approach identifies relevant irregularities and remedies only the *relevant* ones. We show that the relevance of an irregularity depends on the position of the sink in the network. Developing such techniques is the target of this paper. We primarily focus on sparse deployments as they are vulnerable to frequent and varied topology irregularities. In dense networks, where duty cycling is normally used, our approach can support the identification of sensor nodes to duty cycle.

Overall, the benefits of repairing the topology irregularities can be classified into two broad classes, namely network- and functionality-centric improvements. The network operation is enhanced through shorter routing paths, reduced latencies, and balanced and lower energy overhead. The WSN functionalities are optimized by maintaining a regular topology leading to uniform sampling, more accurate information extraction and hence achieving a higher Quality of Information (QoI) [7] level for the WSN objectives. Therefore, we expect our contribution to have a significant impact on the network and application design in WSN as well as their deployment.

In this paper, we propose a novel WSN approach for initial/additional sensor node placements to achieve efficient, sustainable and low cost provisioning and maintenance of regular WSN topologies. The proposed strategy is effective for mitigating topology irregularities resulting from sensor node failures. The maintenance depending on available supplemental resources can be provided manually (static network) or be automated (if some/all sensor nodes can be remotely repositioned). To our knowledge, we are the first to provide an efficient and tunable maintenance strategy for a sustainable topology regularity of sparse WSN deployments. The proposed technique, i.e., Topology Oriented Maintenance (TOM):

- efficiently detects topology irregularities and provides maintenance options for a sustainable regular topology,
- is tunable and allows setting bounds on the tolerable level of topology irregularity,
- is localized, thus, allowing for efficient and sustainable WSN self-healing, and
- provides means for a balanced and minimal initial WSN that fulfils the requirements.

We validate TOM qualities with an extensive set of evaluation studies. We show TOM effectiveness at reducing the discrepancy between hop and Euclidean distances, balancing the energy usage and shortening average hop distance to the sink. We demonstrate that TOM effectively and efficiently maintains an overall regular topology by enhancing an initial sparse WSN. Thus, TOM outperforms the costly approaches that require a certain level of redundancy in node deployment.

We structure the paper as follows. The related work is discussed in Section II. Following the system model in Section III, we present a precise formulation of our objectives and requirements in Section IV. Section V details the proposed TOM technique as the paper's main contribution. The evaluation is presented in Section VI.

II. Related Work

There are many overt indicators for topology irregularities. The most obvious and severe case being network partitioning, where parts of the WSN gets disconnected from the sink. The main goal of connectivity maintenance algorithms is to establish or to restore the full connectivity [8]–[12] so that paths exist between pairs of sensor nodes. *K*-connectivity is a preventive measure which requires the existence of *k* alternative paths between each pair of sensor nodes [13]–[15]. Preventive techniques also try to avoid disconnections by predicting energy dissipation patterns and performing re-/deployment and energy provisioning [16]–[19] or balancing communication [20]. The deployment of dedicated relay nodes also may extend the network lifetime [21], [22]. While useful for restoring/preserving prior state of the network, all these approaches do not address the core issue of eliminating relevant irregularities. The approaches [10]–[12] try to minimize the number of supplemental nodes required for reconnecting network partitions. They often create another irregularity, since the reconnection targets only providing connectivity, e.g., by adding a single node as a connectivity bridge. These techniques primarily are centralized and less effective at considering the distributed and dynamic state of the network (e.g., energy level to assure stable connections). Their common trait is that they focus only on the existence of paths while neglecting the topology irregularities. Other related techniques aim at improving the goodness of connectivity via adding relay nodes [23], [24]. These approaches search for locations to place relay nodes that increase the Fiedler value - an indicator for the goodness of the connectivity. Unfortunately, they are centralized and focussed on inter-sensor-nodes end-to-end communication, which is not typical for WSN.

Another indicator of topology irregularities is the appearance of critical [3] / bottleneck nodes [4]. While the information about their location is important, it is not sufficient to solve the irregularity problem. The topology irregularities also pose a problem for geographic routing protocols. The general strategy is to minimize the impact of the irregularity by avoiding the paths that pass by the anomaly [25], [26].

Topology irregularities can also influence the functionality of some applications such as sensing coverage preserving approaches. The sensing coverage problem assumes that each sensor node can sense/detect the occurrence of a certain event in the given sensing radius. Therefore, the goal is to deploy the WSN so that each position of interest is within the sensing radius of at least one sensor node [27]–[32] or to model the coverage holes [33] or to detect the coverage redundancy to conserve resources [34]–[37]. Several surveys [38]–[40] describe the techniques for achieving network coverage and identify three main classes: a) Voronoi based, b) virtual forces, and c) grid based. If the communication range is twice the sensing range, the network coverage implies connectedness [41]. Using this principle (to indirectly assure topology regularity) entails a high number of resources and lacks tunability to address only relevant irregularities. Moreover, the demand for additional resources is even higher when the WSN application does not require full coverage. Sensing coverage driven approaches consider only the sensing non-coverage irregularity. We propose an approach that (a) is greedy in defining a set of supplemental nodes, and (b) systematically repairs varied topology irregularities.

Topology control techniques [42], [43] aim at designing optimal routing trees based on a given topology. Neighboring sensor nodes are chosen as parent/children pairs or the transmitter power control is utilized to provide requested paths. Hence, topology control can be considered as a pre-deployment design technique aiming at minimizing energy depletion rather than a maintenance approach. Our work recognizes the physical limits of a deployed topology that cannot be overcome by this class of techniques. The applicability of topology control techniques for maintenance is limited only to special circumstances. For instance, increasing the communication range through increasing the transmission power allows restoring connectivity. However, upon reaching the maximal communication range, the topology control technique obviously cannot further influence the WSN properties.

III. System Model

Conforming to contemporary WSN models, we assume a WSN consisting of n resource constrained sensor nodes and a sink. The sensor nodes have finite battery energy and usually possess limited processing and storage capabilities.

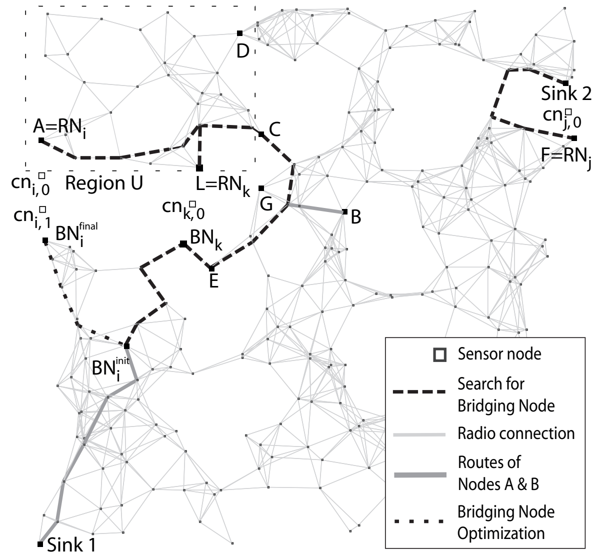

Fig. 2. Topology irregularities in a sparse deployment example

The communication range R is limited and fixed for a given deployment. Two neighboring sensor nodes can communicate directly only if their Euclidean distance is smaller than R. This communication dominates the imprint on the energy depletion of the sensor nodes. We assume that the initial sensor deployment is sparse. The sensor nodes know their position using on-board GPS receivers or alternative GPS-free techniques of localization [44]. We consider cases where (a) all nodes are static, or (b) a mix of static and nodes of controlled mobility. Our model implicitly considers sensor node failures and duty cycling as this is equivalent to relocating a sensor node. We define the network lifetime as the time elapsed from the deployment till the first partitioning of the network. We assume that sensor nodes know their hop distance to the sink, e.g., based on a shortest path tree routing. We consider that sensor nodes are aware of the presence of their 1-hop neighboring sensor nodes, including their position and hop distance to the sink.

IV. Objectives and Requirements

In WSNs it is crucial to provide balanced resource usage to assure longest possible network lifetime. It is especially evident for a sparse network where the low connectivity degree usually leads to the creation of lengthy routing paths. As shown in Fig. 2 the routing path of *Node A* (to *Sink 1*) vastly differs in length from the routing path of *Node B* (to *Sink 1*) although both are placed at comparatively equal Euclidean distances to the sink. A longer route translates in higher energy cost of sending data to the sink. Additionally, the lack of straight path to the sink means that the route has to be shared with many more sensor nodes (*Region U* in Fig. 2) than in the case of a regular topology. As a consequence sensor nodes, such as *Node C*, are under an additional burden and serve as focus points for routing protocols. Their energy becomes discharged much faster and may lead to network partitioning.

Our goal is to provide a distributed technique for finding possibly few re-/deployment locations, where the placement of new sensor nodes or the repositioning of mobile nodes will restore a balanced energy usage and data traffic. While we directly target only the discrepancy between Euclidean and hop distances, the reduction of that metric improves many QoI aspects of WSN such as lifetime, latency and data accuracy.

The provided solution should be tunable in regard to the extent of irregularities it can tolerate. Also the relevance of the irregularity should be taken into consideration. For instance, the position and orientation of irregularity in relation to the sink should be considered. While *Region U* is affected by the irregularity in relation to *Sink 1*, it does not exhibit adverse effects in relation to *Sink 2*. An opposite situation takes place in case of *Node F*. In relation to *Sink 1* it is only marginally affected by the irregularity, but in case of *Sink 2* the effects of the irregularity are evident (extended routing path to *Sink 2*). Moreover, this technique should limit the amount of resources required for maintenance. For this purpose it is crucial to provide feedback regarding the possible gain from a certain maintenance option (extent to which the topology is improved, e.g., reduction in hop distances to the sink) and its cost (resources required to complete maintenance). The proper evaluation of the gain requires inclusion of the localized information, e.g., the actual sensor data volume. This feedback value could be treated as a normalizing weight. In case of limited resources TOM should allow to allocate them according to the best tradeoff between potential gain and costs.

V. TOM: Topology Oriented Maintenance

After an overview of our approach, we detail techniques for discovering the sensor nodes that are most affected by topology irregularities. Subsequently, we describe the search process for finding a suitable part of the network where new connections could be established to repair the irregularity. We present optimizations for this search process and techniques for local evaluation of possible reconfiguration gains.

A. Overview of our Approach

The primary step for providing an appropriate maintenance of the topology is the identification of those sensor nodes that suffer from an irregularity in the topology. As mentioned earlier the hop distance discrepancy is an appropriate indicator of *relevant* irregularities *independent* from their cause. Accordingly, the sensor nodes that suffer at most from irregularities are: (a) Sensor nodes whose hop distance shows a discrepancy that exceeds a certain threshold, and (b) nodes that have no hop discrepancy, however, they have to relay the traffic of those nodes that suffer from discrepancy. We refer to sensor nodes that show the highest discrepancy in their hop distance as Reconnecting Nodes (*RN*) (e.g., RN_i in Fig. 2). Their selection is influenced by tunable parameter set to determine acceptable extent of irregularities. Therefore, they are the first to be considered for bridging to the closest part of the network where a regular topology may be maintained. Further network/node properties should also be taken into consideration while selecting RNs, e.g., residual node energy. There are disadvantages of using an energy constrained sensor node as an RN, as this sensor node would forward the data from senor nodes in its neighborhood, significantly increasing energy depletion rate.

The selection of the sensor nodes, to which RN could be reconnected is the second step of topology maintenance. The algorithm starts with the RNs and locally traverses the topology in the direction of sink searching for the sensor nodes, which are located in the part of the network where regularity is maintained. The sensor nodes are selected under the condition that the newly established connection (between RN and the selected sensor node) reduces the distance discrepancy to the acceptable level (after maintenance the indicator of irregularity will fall below a specific threshold), determined by the network operator (tunable parameter). We refer to such a sensor node as a bridging node (*BN*) (e.g., BN_i in Fig. 2). Also in this case it is valuable to consider the energy level of the BN candidate. After performing topology reconfiguration BN will have to forward messages from the reconnected area. Therefore, it is essential that BN has enough energy to fulfill its role. We refer to the set of sensor nodes placements proposed by TOM to connect RN and BN as Connecting Nodes $CN_i = \{cn_{i,0}, ..., cn_{i,j}\}$.

Not all proposed reconfigurations are equally important and beneficial to the topology regularity. Some of the reconfigurations may be redundant. For example, maintenance may apply to the region of low phenomenon activity, and as consequence the added sensor nodes would transport only low volume of data, which may not justify the maintenance cost. It is especially important to provide the feedback based on localized data for the scenarios where resources for providing maintenance are limited and need to be prioritized. The goal of the last step is to determine the importance of each given reconnection option by weighting its impact on the topology. The weighting may include single or a set of factors (e.g., hop distance reduction, data transport volume, etc).

B. Discovery of Topology Irregularities

We note that the repair of an irregularity that is closer to the sink may resolve the regularity perceived by nodes that are farther from the sink. Therefore, we propose that the discovery process should trigger depending on sensor node distance from the sink. The farther from the sink the later should the discovery process start.

We should identify the sensor nodes, whose reconnection to the closest part of the network with regular topology will bring highest gain in balancing topology distances. To this end, we look for sensor nodes whose discrepancy between Euclidean and hop distance is locally maximal. To estimate the extent of the Euclidean and hop distance discrepancy, we calculate the sensor node discrepancy indicator f_i (Eq. (1)).

$$f_i = R - \frac{\delta_{sink,i}}{hop_i \cdot \theta} \tag{1}$$

hop_i is the hop distance of Node i from the sink, θ $(0 < \theta < 1)$ is the tunable parameter that expresses the fraction of the communication range R that one hop covers on average in a single transmission, and $\delta_{sink,i}$ is the Euclidean distance of Node i from the sink. f_i effectively shows the magnitude of the detour of the route from Node i to the sink under the stated θ parameter for communication range utilization. Therefore, f_i represents an indicator for topology irregularities and we utilize it to measure how much communication range is lost on average by each hop within a given route. The higher the value of f_i the larger the discrepancy between Euclidean and topology induced distances, and the longer the route detour. At first, Eq. (1) would lead to the following counterintuitive perception: f_i increases with R. However, it should be noted that the connectivity increases with R. Consequently the number of hops (hop_i) decreases with R, thus, offsetting the increase in R. We define f_{TH} as a threshold discrepancy value so that for a given Node i if $f_i > f_{TH}$ we state that Node i is located in a network region experiencing a topology irregularity.

After fixing the indicator of topology irregularities it is necessary to find the local maximum of f_i. The sensor node with the maximum value is the one that should be reconnected to a closer regular part of the network. At this point we should also assure that the selected sensor node is capable of assuming its role of RN, e.g., it has sufficient energy level. Therefore, we choose only amongst the sensor nodes whose $f_i > f_{TH}$ and whose energy level $E(i)$ is higher than a given threshold E_{TH}. Each sensor node calculates its f_i value as well as those of its neighbors (using the collected neighborhood information) and calculates their overall maximum. If the maximum value f_i exceeds f_{TH} and the energy level is above E_{TH} then the value is transmitted to all 1-hop neighbors. Only a sensor node that receives from all its 1-hop neighbors a value which is (a) lower or equal to its own, (b) higher than f_{TH} and (c) has a residual energy level above E_{TH}, is designated as RN.

This discovery process is based solely on local information that is updated upon changes in topology. The necessary data for this phase of TOM can be collected using piggy-backing. The event triggered for the re-evaluation of the f_i value takes place only upon changes of routing paths, establishing new routing paths to a new sink (e.g., in a multi-user scenario), or upon sending the f_i value by one of the neighbors.

C. Search for Bridging Nodes

After completion of the discovery phase, an RN can start the second phase of *Search for Bridging Node* (Algorithm 1). In this phase, the current topology is locally explored to find the BN. The search occurs in two steps: (a) *Initial search*, where the topology is explored to find an initial candidate for assuming BN role, and (b) *Bridging Node Optimization*, where further sensor nodes are considered to shorten the distance between the bridging and reconnecting nodes.

1) Initial Search: We first present a simplified version of the search algorithm that does not consider the updates to the topology by other RNs. The strategy is to explore the path by circling the topology irregularity which is the source of the discrepancy.

$$\alpha_{i,j} = arctan(\frac{i.y - j.y}{i.x - j.x}) \tag{2}$$

$$\beta_{i,j,k} = \alpha_{i,k} - \alpha_{i,j} \tag{3}$$

The main idea is to circumvent the irregularity using a strategy inspired by geographic forwarding. The search also includes optimizations to skip some border nodes that otherwise would extend the search path (*Node G* in Fig. 2). The search tries, as possible, to maintain a constant heading in order to reduce the hop distance for locating the targeted regular network region.

Algorithm 1 Search for Bridging Nodes

function SearchPath(curNode, prvNode) : **BridgingNode**
var candCW, candCCW, candNode;
// search for closest (counter)clockwise angular neighbor
for all sn **in** Neighbors(curNode) **do**
    if β(curNode, sn, prvNode) $<$ β(curNode, candCW, prvNode) **then**
        candCW = sn;
    end if
    if β(sn, curNode, prvNode) $<$ β(candCCW, curNode, prvNode) **then**
        candCCW = sn;
    end if
end for
if candCW.hop $<$ candCCW.hop **then** // find neighbor closer to sink
    candNode = candCW;
else if candCW.hop $>$ candCCW.hop **then**
    candNode = candCCW;
else if $\delta_{candCW,sink} < \delta_{candCCW,sink}$ **then**
    candNode = candCW;
else
    candNode = candCCW;
end if
if $\delta_{RN,curNode} + hop_{curNode} \cdot R \cdot \theta < \frac{\delta_{sink,RN}}{\theta}$ **and** $E(curNode) > E_{TH}$ **then**
    return candNode;
end if
return SearchPath(candNode, currNode); // hand-off to next candidate

An RN first establishes its angle ($\alpha_{RN,V}$) in the relation to the previous visited Sensor Node V (initially V = sink) using Eq. (2). Then, searching across its neighboring sensor nodes, it looks for two sensor nodes whose angle distances are minimal in clockwise $\beta_{RN,m,V}$ and counterclockwise $\beta_{m,RN,V}$ directions. One of the two (one if RN has only a single neighbor) closest radial neighbors is the possible next sensor node to explore while searching for the BN. The search process follows the path of the sensor node whose hop distance to the sink is smaller. If the hop distances of both candidates are equal, the next sensor node to explore will be chosen as the one placed closer to the sink w.r.t. to the Euclidean distance. In an unlikely event, as confirmed by simulations, if the search process revisits a sensor node, then opposite choice regarding the selection of next sensor node is made. The search continues until (a) Inequality (4) is valid, where $\delta_{i,j}$ represents the Euclidean distance between two nodes *i* and *j*, and (b) the energy level of the considered node is larger than E_{TH}. Each sensor node on the search path sends a single message. The number of hops required for performing initial search in worst case does not exceed the hop distance from sink, as the sink is the ultimate bridging node.

$$\delta_{RN,i} + hop_i \cdot R \cdot \theta < \frac{\delta_{sink,RN}}{\theta} \tag{4}$$

2) Virtual Search: When an RN searches for a proper BN, it may happen that some other RN has already executed the search process and created alternative routing paths. It would be beneficial to use this information when searching for BN. Instead of connecting the isolated part of the network directly to a region with regular topology, it can be connected to the part of network where the connectivity balance has already been restored. Therefore, the reconnecting links become shorter and require less sensor nodes. Using the prior paths also accelerates the search process.

For this goal, we have modified the `Neighbors()` function (Alg. 1 L. 4). Instead of considering all neighbors as potential next steps in the search algorithm, we select only their subset. If some neighbors already have alternative routes to an RN, we check if in the worst case scenario connecting directly to that RN would allow to fulfill the stated requirements. In such cases, we allow the `Neighbors()` function to choose only from such neighboring sensor nodes that have such an alternative route. If some neighbors have two alternative routes to different RNs then we select the neighbor which yields a lower value of Eq. (5) and do not consider the other neighbors anymore. In case the paths via the neighboring sensor nodes with alternative paths are selected, only the virtual hop distance is needed, i.e., distance to selected RN plus RN's distance to the sink. This virtual hop distance is then further used for optimizing the selection of BN.

Algorithm 2 Optimized Selection of Bridging Nodes

function OptimizeBridge(curNode) : **BridgingNode**
var candNode = **nil**;
var minDist = $\delta_{curNode,RN}$;
for all sn **in** Neighbors(curNode) **do** // look for best BN candidate
    if $E(i) < E_{TH}$ **then**
        continue;
    end if
    curDist = $\delta_{curNode,RN}$;
    if $\delta_{RN,sn} + hop_{sn} \cdot R \cdot \theta < \frac{\delta_{sink,RN}}{\theta}$ **and** curDist < minDist **then**
        minDist = curDist;
        candNode = sn;
    end if
end for
if candNode != **nil then** // if candidate found, try searching further
    return OptimizeBridge(cand);
end if
return curNode; // hand-off to next candidate

3) Optimization of the Selection of Bridging Nodes: After executing Algorithm 1 the initial Bridging Node (BN^{init} in Fig. 2) is found. Although the BN^{init} complies with the requirements to restore the route balance, there could still be a better candidate (closer to RN) to act as a BN. The optimization is to find the sensor node that is possibly closest to RN (w.r.t. the Euclidean distance) and still fulfills the requirements of BN ($f_i < f_{TH}$ and $E(i) > E_{TH}$). Algorithm 2 checks among all neighbors of the current BN if any of them also fulfils the conditions of acting as a BN. If such sensor nodes are found, then the one with the minimal distance to RN is selected. Algorithm 2 then re-initiates with this selected BN value. If no better candidate for acting as BN is found then the current sensor node becomes the final BN (BN^{final} in Fig. 2).

4) Local View Update: The RN, when initiating the search process, can use its new virtual hop distance to the sink (Eq. (5)) that it will have after connecting to the BN. This new virtual value needs to be propagated to all the sensor nodes in RN neighborhood as the hop distance of these sensor nodes will also get reduced. This propagation process resembles a classic spanning tree construction algorithm with a few optimizations to reduce the message traffic. The RN starts a local broadcast sending a message containing the expected hop distance to the sink. Each sensor node receiving the message checks whether the new path proposed by RN is shorter than the current one. If this holds, the new path is added to the routing table pointing to the RN as root. Each sensor node also decides whether to further broadcast the message. If any of the neighbors can benefit from the new routing path, then the message is forwarded, otherwise it is suppressed. The broadcast message can also be suppressed when it traverses more than a given limit of hops hop_{TH}. That can be interpreted as the scope of the update is large enough to render this repair a priority. Each sensor node sends only a single message if the new path can influence routing of any of its to be children.

$$vhop_i = \lceil \frac{\delta_{i,sink}}{R \cdot \theta} \rceil - 1 \tag{5}$$

Depending on the extent of the irregularity the initial reconnection may be insufficient to completely recover from irregularity consequences. After performing local view update sensor nodes are aware of their new virtual distance to the sink. Still some of the updated f_i (e.g., f_i of *Node L* in Fig. 2) updated using the new virtual distance may remain above f_{TH}. Such sensor nodes initiate a new discovery and search procedures that should lead to further minimizing the impact of topology irregularity. The TOM execution progresses iteratively as long as one sensor nodes still suffers from the topology irregularity with regard to the parameter θ.

5) Update Weighting: After the update process finishes, the impact of newly proposed topology adjustment needs to be weighted. Weighting is performed to provide feedback on the importance of the update to the WSN operator or mobile nodes within the network to make the decision upon executing maintenance. In order to normalize the new route, an additional set of factors may be incorporated (e.g., reduction in hop distances, volume of transmitted data, phenomenon activity level). Initially, we consider the reduction in hop distances for all sensor nodes benefiting from the topology adjustment. For this purpose, each of the sensor nodes that improved its path sends a message containing the number of hops reduced in its path.

Over the *local view update* phase, each sensor node can ascertain whether any of its neighbors benefits from the route update. Hence, it waits for their response message about the obtained reduction. It may happen that a sensor node did not receive a response because the other sensor nodes sent their response along a shorter route. Such a sensor node can observe these responses and if necessary it starts itself the response process. Each intermediary sensor node aggregates the data collected from its children. When it receives data from all its children or sniffs that the children already has responded to other nodes, then it forwards the aggregated data to its own parent. At the end of the weighting process the RN receives a single number describing the weight of the gain from bridging the gap in the network.

6) Bridging: When both RN and BN have been determined, the number and positions for the connecting nodes CN_i still have to be decided. A cost effective approach is to connect RN and BN in a straight line, placing the connecting nodes at equi-distant positions. The number (h) of connecting nodes needed depends on the communication range and the coefficient λ ($0 < \lambda < 1$) describing the fraction of usable range of the communication range. λ generally takes values close to 1 meaning that the added sensor nodes utilize the full communication range as the deployment is assumed to take place in a controlled manner. If the placement is semi-automated and depends on the estimated localization, the λ value may be lowered to reflect that condition. h is calculated using Eq. (6);

$$h = \lceil \frac{\delta_{RN,BN}}{R \cdot \lambda} \rceil - 1 \quad (6)$$

After placing the connection nodes, the BN should either trigger update mechanism of underlying routing protocol or initiate local broadcast to update the topology with new routing path utilizing added connecting nodes. The update/broadcast will immediately stop at sensor nodes that do not benefit from added sensor nodes and only propagate to those which do.

VI. Performance Evaluation

We now describe the evaluation settings and metrics guiding our decisions.

A. Evaluation Settings

We consider a WSN network consisting of 270 sensor nodes, with communication range $R = 3m$, deployed over the area of 30m × 30m. We gradually change the value of θ from very relaxed regularity $\theta = 0.65$ to very strict one $\theta = 0.95$. We also vary the number of sensor nodes from 200 (sparse scenario) to 300 (dense scenario) in order to measure the utility of TOM under different network densities. We use our stand-alone implementation to simulate the TOM approach.

B. Evaluation Metrics

We address the problem of network relating the topology irregularity to the affected WSN properties. The objective purpose of the presented metrics is to show the efficiency of the proposed TOM approach in improving these properties.

In order to quantify the topology regularity improvement for the observed discrepancy between the hop and Euclidean distances, we use a mean square error (MSE) based metric calculated as follows. From the actual Euclidean distance we subtract the topology induced hop distance and calculate the square value. Then, we sum the value for all deployed sensor nodes. We measure the percentage reduction in MSE value before vs. after executing TOM (*Distance*). This percentage reduction is compared against the reduction achieved using the strategy based on random deployment of the same number of sensor nodes as added by TOM (*Rnd Distance*).

Similarly, we quantify the energy balancing properties of TOM. We calculate the square value of the difference between the initial energy supply and remaining energy after performing an arbitrary number of data collection rounds. We then sum the value for all deployed sensor nodes. As for previous metric we measure the metrics percentage reduction between original deployment and this after applying TOM (*Energy*).

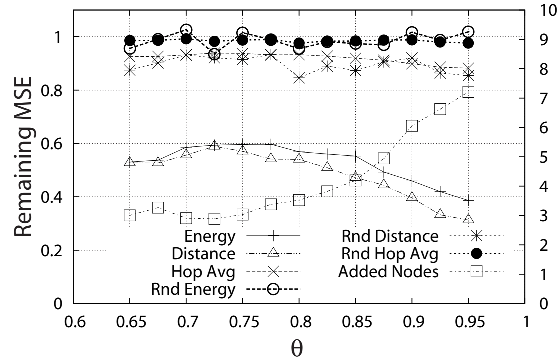

Fig. 3. TOM Tunability to repair irregularities of varied severity

To show the energy saving and latency reduction we compare the average hop distance to sink (using shortest path tree routing) before and after executing TOM (*Hop Avg*). Each saved message transmission translates into lower energy expenditure. A shorter route also means a shorter latency.

The goal of the last two metrics is to quantify the achievements of TOM for applications that use the Voronoi abstraction [45]–[47]. For that purpose, we let the WSN compute the Voronoi diagram based on 2-hop neighborhood knowledge. We execute Voronoi computation before and after completing the maintenance as proposed by TOM sensor nodes. In the former case, added sensor nodes are omitted while calculating the Voronoi diagram. They are only utilized for communication between original sensor nodes. The first metric (*False Lines*) is directed at measuring the proper identification of Voronoi neighbors [47]. We sum for each sensor node the square value of misclassified Voronoi neighbors and the result is divided by the number of sensor nodes. We measure the percentage reduction in these values before and after executing TOM. In the second metric we use an MSE based metric (*Surface MSE*) to show how much the areas of the Voronoi diagrams differ from the optimal one [45]. From the properties of the Voronoi diagram implicitly follows, that the area size of polygons obtained using complete topology information is minimal. Therefore, we calculate the area of each Voronoi diagram for each sensor node and subtract the area size of optimal Voronoi diagram. We sum the square values and divide them by the total number of sensor nodes. We measure the percentage reduction in these value before and after executing TOM.

C. Evaluation Results

We divide the results in two classes. The first class represents the impact of TOM on network-centric properties of the WSN. The second class shows the functionality-centric benefits of maintenance using TOM.

We first show the tunability property of TOM for controlling the extent of topology irregularities. Fig. 3 shows that even for fairly relaxed requirements ($0.65 < \theta < 0.75$) TOM reduces the MSE of *Energy* and *Distance* metrics to 60% of its original

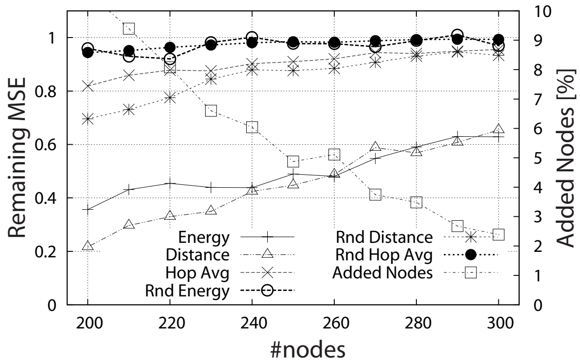

Fig. 4. Impact of the network size

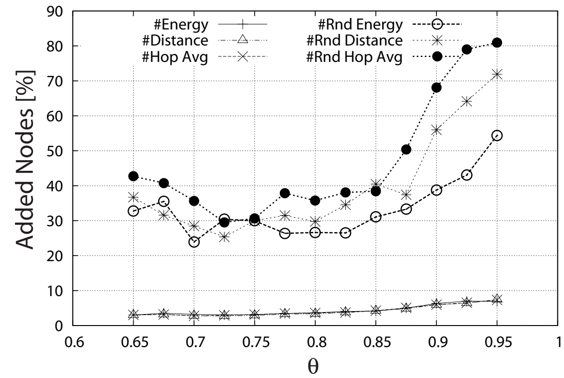

Fig. 5. Comparison with random deployment strategy

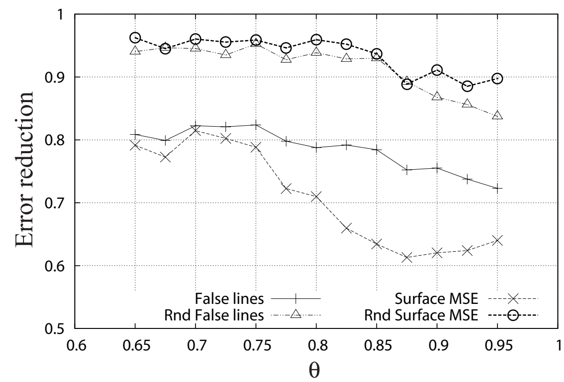

Fig. 6. Impact on Voronoi diagram calculation

value, balancing the energy usage among the sensor nodes and hop distances to the sink. The reduction progresses further with the increasing θ reaching in the end as low as 30% compared to the case without maintenance. These improvements of network properties come at the cost of increased resources demand, which over $\theta = 0.85$ steeply increases. For most cases to maintain the network only approximately 3% - 4% of original number of deployed sensor nodes are required. That translates for the given setup to roughly 8 - 11 sensor nodes. Only in the extreme case of $\theta = 0.95$ the need for resources reaches 7% corresponding to 19 sensor nodes. The average hop distance also decreases with increased θ but not so rapidly like other metrics. Nonetheless, it equals to at least 10% decreases in hop distance. By average distance of 11 hopes this corresponds to a drop of 1 hop from the route on average. The accumulated effect for all sensor nodes translates in the reduction of 270 transfer hops. The maintenance based on random strategies (*Rnd Distance, Rnd Energy, Rnd Hop Avg*) shows no improvement of the properties of the network.

The performance of TOM is also closely related to the network size (number of sensor nodes deployed). In order to illustrate this relation, we keep the previous deployment settings and fix the value of θ to 0.85. Then, we gradually change network size from 200 sensor nodes, generating very sparse but still connected networks, up to 300 deployed sensor nodes, representing relatively dense deployments. As concluded easily from Fig. 4 the possibility to lower the MSE value of metrics decreases (*Energy, Distance, Hop Avg*) with the increase in the density of the network. The demand for resources follows these trends in reverse (*Added Nodes*), meaning that at higher node densities, less resources are needed to maintain a regular topology. The obtained results confirm the expectations. In a denser network the occurrences of irregularities are rare and therefore also the need for their reduction subsides. Even if irregularities appear their magnitude is limited and as a consequence they do not require large number of resources to tackle them. In contrast, the maintenance executed using the random strategy (*Rnd Energy, Rnd Distance, Rnd Hop Avg*) and deploying equal number of sensor nodes only marginally improves the topology of the network and remains mostly independent of the network density.

Next, we illustrate the deployment cost savings provided by TOM. For this purpose, we randomly deploy additional sensor nodes until the simulation reaches the same properties as achieved using TOM for a specified θ. Then, we calculate how many sensor nodes need to be added in comparison with the original deployment. Fig. 5 clearly indicates that for any of the presented metrics, providing the same results as TOM by random dropping of sensor nodes is very expensive. For θ ranging from 0.65 to 0.85 the demand for randomly deployed sensor nodes varies from 30% to 40% of the initial number of sensor nodes. For θ larger than 0.85 the demand drastically increases from 70% for *#Rnd Distance* up to 80% for *#Rnd Hop Avg* to keep up with TOM. For the *#Rnd Energy* situation is a bit better, but still it requires over 40% and up to 50% of additional sensor nodes. For comparison, we added also the plots of the TOM approach. In this case, for the whole range of θ and each applied metric, the demand for new sensor nodes never exceeds 10%.

To show the functionality-centric aspects of maintenance, we evaluate the impact of implementing the TOM strategy on the performance of the Voronoi diagram construction with 2-hop neighborhood knowledge. Fig. 6 depicts the achieved performance for the applied metrics. The *False Lines* metric shows that TOM is capable of reducing its value close to 20% for lower θ and over 25% for higher values of θ. The higher number of sensor nodes placed to increase regularity results also in better communication in the sensor nodes neighborhood, allowing for better identification of the Voronoi neighbors. Random deployment also leads to reduction in the value of this metric but it significantly underperforms TOM.

The same holds for the *Surface MSE* metric which shows how the Voronoi area size is approximated. For the values of θ up to 0.75 the reduction of *Surface MSE* metric mimics that of *False lines* metric. For higher values of θ the reduction progresses at faster pace and reaches up to 35% lower value of the *Surface MSE* metric. Also in this case TOM outperforms the random deployment (*Rnd Surface MSE*), even with larger margin.

VII. Conclusions and Future Work

We have presented TOM, an efficient distributed strategy for topology optimization driven maintenance. Using localized information, TOM is capable of detecting the relevant and varied topology irregularities in a deployed WSN. In addition, TOM searches for the suitable placements of additional or redeployable or mobile nodes that allow the optimization of the topology regularity and its maintenance. The immediate benefits from applying the proposed maintenance strategy are balanced energy usage, shorter routes, longer network lifetime and lower latency for message transport. We also showed that applications using the Voronoi abstraction benefit from regular topology by providing better accuracy.

We plan to extend the TOM approach to consider functionality centric and application based objectives while performing topology optimizations. In particular, maintenance should assure not only topology regularity in the direction to the sink but also in the areas of interest desired by the application.

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