

Impact of Scalability and Density on Lifespan of Energy-Efficient Wireless Sensor Networks

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Abstract. Sparse and dense wireless sensor networks (WSNs) are both broadly implemented due to the rapid advancement of control and communication technologies. Impact of both scalability and density on the lifespan of WSNs has however seldom been examined which depends on the sensor node deployment. Scalability takes a critical role in both the connectivity and coverage range of WSNs, which in turn is also relevant to the lifespan defined in terms of either the first node or last node. Without loss of generality, to minimize the power consumption and optimize the WSN lifespan, energy-efficient WSNs are selected to analyze the impact of scalability and density on the WSNs lifespan in this research. When path transmission energy and transceiver circuit energy are both taken into account, it is not guaranteed that either single-hop routing or multi-hop routing is always optimal. In general, single-hop routing is more efficient for WSNs in small diameter coverage range at high radio transceiver power, while multi-hop routing is more efficient for WSNs in large transmission distance at low radio transceiver power. As a matter of fact, the single-hop routing is chosen for WSNs analysis with respect to density and scalability in this preliminary study, which can also be easily expanded to multi-hop routing cases.

Keywords: wireless sensor networks, power control, hierarchical clustering, adaptive clustering, scalability, density, sparse deployment, dense deployment, lifespan

1 Introduction

Wireless sensor networks consist of numerous spatially placed sensor nodes, which are small battery powered autonomous devices capable of data processing and short range radio communication. Wireless channels are used for transmitting and receiving data among sensor nodes. Network densities of WSNs vary significantly from sparse to dense deployment. Integration of sensing, communication, control, computing and hardware technologies makes it possible to produce compact scale and low energy devices, which allows for the capability of dense deployment. WSNs are subject to limitation of battery power, operating power and memory storage as well as the delay, propagation loss, and interference. For dense deployment of WSNs such as wireless

cellular networks, information redundancy upon broadcasting also needs to be taken into account [1-3].

The low energy adaptive clustering hierarchy (LEACH) is developed to evaluate performance in terms of WSNs lifetime, quality and latency. The distributed processing is enabled to save energy resources via cluster self-organization, adaptive clustering, cluster head rotating and balanced energy load distribution as well as the application-specific aggregation of data. However, practical node heterogeneity and cluster head load imbalance will shorten the network lifetime. Meanwhile it is based on single-hop instead of multi-hop data transmission. In this case, energy-efficient protocol is necessary for potential optimal clustering with energy-constrained sensor nodes, where nodes with highest residual energy are reelected as cluster heads in next rounds in order to forward the data to base stations [4]. The initial LEACH protocol can be enhanced from different aspects to extend the lifetime. The near-optimal chain-based protocol has been used to optimize sensor energy efficiency via power-efficient information gathering. Each sensor node solely communicates with its nearest neighbor and then it takes turns to transmit data to the base station. It reduces the energy consumption each round [5]. The multi-hop LEACH protocol via clustering is also proposed which outperforms the LEACH protocol in terms of energy consumption, lifetime and stability. The heterogeneous nodes are used for data transmission following the optimal path from cluster heads (CHs) to the base station (BS) [6]. In addition, an energy-efficient clustering protocol is designed for the heterogeneous WSNs using data aggregation. Reelection of cluster heads and selection of the suitable routing path for data transmission are both based on the residual energy of sensor nodes [7].

The balanced data aggregation scheme can be introduced via clustering. The sensor network is split into a number of rectangular grids. One cluster head per grid is elected for load balance among sensor nodes as well as node management in WSNs [8]. An energy-efficient reliable data aggregation scheme can also be designed with clustering. Cluster head is elected based on residue energy and transmission distance from the node to coordinate node. Afterwards it conducts data aggregation to transmit data to the base station [9]. For cellular networks, direct sink access is applied to mobile data collection via clustering. Clustering and data correlation help cluster heads to operate under small overhead and medium access control. Across a wide range of parameters, latency and energy consumption are remarkably reduced with robustness [10]. Sensor node deployment is confronted with diverse harsh environments. WSNs also differ in node densities between sparse and dense deployments. For dense node deployment, broadcasting by flooding will give rise to information redundancy. Thus adaptive routing protocols are necessary. WSNs topology control by integrating adaptive schemes and Kalman filters is proposed to solve these problems [11].

The energy efficiency of WSNs plays a critical role in the lifespan. Data aggregation is important to reduce redundancy and decrease transmission cost to save energy. There is a tradeoff among reliability, energy usage and latency. Dynamic routing is introduced to reach good performance via adaptive clustering. The generalized Ant Colony Optimization (ACO) is used to extend the actual lifespan of sensor nodes with energy constraints. Every sensor node computes the residual energy so as to dynamically estimate probabilities for optimal channel selection to extend the WSNs lifespan

[12]. The music-based harmony search optimization is also designed and implemented in real time for WSNs. Its objective is to optimize the energy distribution by minimizing the intra-cluster distances between cluster heads and members to extend its lifespan. This protocol shows better results than the LEACH protocol and Fuzzy C-Means clustering scheme [13]. Single-hop routing has the merits of less packet loss and propagation delay than others, while its energy efficiency could also be higher than multi-hop routing in many cases, thus it is selected to examine the impact of scalability and density on the network lifespans.

2 Energy dissipation model of WSNs

To successfully transmit and receive a single packet of size K , the energy dissipation is formulated as (1).

$$E_T(d, K) = K \times (E_{TR_ELE} + E_{DA} + E_{AMP} + E_{RE_ELE}) \quad (1)$$

where $E_T(d, K)$ refers to the total energy dissipation to send and receive a packet of the data size K [Bits]; E_{TR_ELE} [J/Bit] refers to the overhead energy of transmitter electronics (e.g., modulation, digital coding, phase lock, filtering); E_{DA} [J/Bit] refers to the additional energy dissipated by cluster heads for data aggregation and compression; E_{AMP} [J/Bit] refers to the radio propagation energy consumed in the power amplifiers which is defined by (2); E_{RE_ELE} [J/Bit] refers to the overhead energy of receiver electronics (e.g., digital decoding, demodulation); d [m] refers to the distance for radio propagation from the transmitter to receiver; ε [J/Bit*m^λ] refers to the transmission amplifier cofactor; λ refers to the path loss exponent.

$$E_{AMP} = \varepsilon \times d^\lambda \quad (2)$$

The path loss exponent λ varies between single path and multiple path propagation. For instance, the free space channel model assigns λ as 2 for single path propagation within the radio range, while it assigns λ as 4 for multi-path propagation in the fading channel model. Particularly λ can be selected as 4 when data transmission starts from the cluster head nodes, while λ is selected as 2 when data transmission starts from other sensor nodes.

For an individual cluster with N sensor nodes, only one will serve as the cluster head (CH) each round. Then the residual energy E_{CH} of the CH must be no less than (3) in order to possibly deliver the data packet.

$$E_{CH} \geq (N - 1) \times (E_{TR_ELE} + E_{DA}) \quad (3)$$

The residual energy E_{RS} of each sensor node is simply the difference between initial energy E_{INI} and the total dissipated energy E_T of that node, as shown in (4).

$$E_{RS} = E_{INI} - E_T \quad (4)$$

The residual energy E_{RS} of any sensor node monotonically decreases along with time unless staying at the idle mode (inactivity). The residual energy of the CH decreases dramatically with exceptional energy dissipation compared with other sensor nodes. To extend the lifespan, reelection of CH must be conducted each round. For LEACH protocol, energy should be distributed evenly, so all nodes will serve as cluster heads with rotation finally. Since the entire network has been split into a number

of clusters covering randomly distributed active nodes and dead nodes, load imbalance among all clusters and CHs will give rise to shortened network lifespan. Thus energy-efficient dynamic routing scheme is needed. The optimality on energy efficiency might be too tough to reach due to numerous factors (e.g., power, memory, propagation loss, delay, latency and interference) under diversified complex cases. Even problems on reaching the optimal number of clusters and optimal number of hops have never been solved completely. The focus here instead is to conduct some preliminary studies about impact of both scalability and density on the lifespan of the simple energy-efficient dynamic routing.

3 Energy-efficient dynamic routing of WSNs

An easily implemented energy-efficient routing protocol has been proposed. In the initial $1/p$ rounds, dynamic routing of WSNs follows the classical hierarchical LEACH protocol. CHs should be determined in advance, which are responsible for data aggregation and transmission. The stochastic scheme (5) is used to generate the threshold so as to determine the CHs. For each sensor node, a random number can be generated ranging from 0 to 1. If this number is less than the specified threshold, then it turns out to be the CH for that round, otherwise it serves as a cluster member for certain cluster head that can provide the maximal signal strength. This threshold θ can be computed by (5).

$$\theta(n) = \begin{cases} \frac{p}{1 - p \left(r \bmod \frac{1}{p} \right)} & [n \in S] \\ 0 & [n \notin S] \end{cases} \quad (5)$$

where p is the desired percentage of cluster heads among all sensor nodes, r is the expected total number of cluster heads in the actual round, S is the set of sensor nodes never being CHs over all previous rounds.

After $1/p$ rounds, the energy-efficient dynamic routing will be applied to substitute the LEACH protocol. The main reason is that an assumption of homogeneous sensor nodes during the setup phase is not feasible for those WSNs with significant large diameters. Most sensor networks are heterogeneous in reality. The residual energy of each sensor node will take the leading role in subsequent cluster head elections and dynamic routing. Specifically, the residual energy of all sensor nodes within each cluster of the setup phase will be computed again and sorted. The one with the largest amount of the residual energy will serve as the new CH in the next round. After all CHs of the next round are updated already, each non-cluster-head sensor node turns out to be a member of an updated cluster whose CH provides the maximal signal strength in the new around. The load imbalance problems can be easily solved accordingly. This simple scheme continues throughout the life expectancy of WSNs.

There are three phases in each round, namely cluster head election and broadcasting, cluster membership setup, and steady state data transmission. During the steady state, cluster heads will aggregate and transmit the data. Data packets can only be

transmitted via active sensor nodes while other sleepy nodes stay idle upon communication in order to save energy. The energy model (1) in fact covers the transmitting energy, propagation path loss energy, receiving energy, aggregating and compression energy dissipation, which is also used to calculate the residual energy.

4 Sparse sensor node deployment

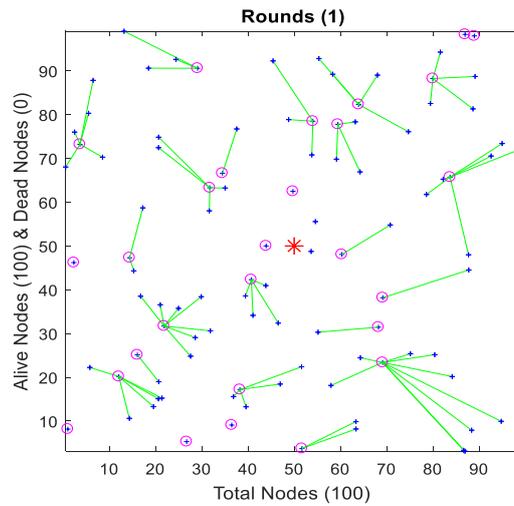


Fig. 1. 100-Node sparse random network (initial round)

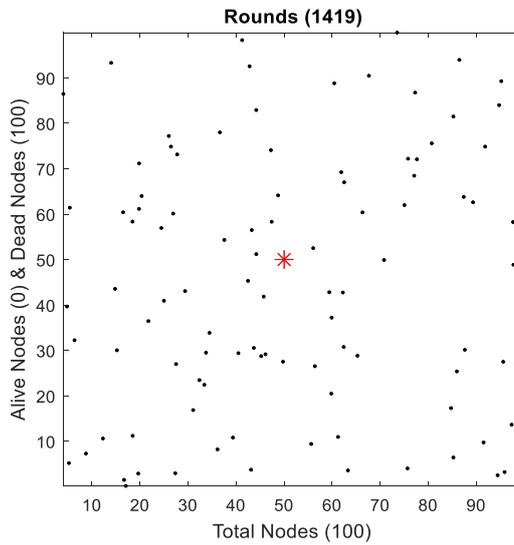


Fig. 2. 100-Node sparse random network (final round)

For all sparse sensor node deployment in this study, the total count of sensor nodes is equivalent to both length and width of WSNs. Numerical simulations have been conducted with some useful results. For instance, it takes about total 1400 rounds for the 100-node sparse random network ($100m \times 100m$) to complete all data transmission in terms of the battery power. The patterns of the initial round and final round are shown in Figs. 1-2, where blue "+", pink "o", red "*" and black "." will represent the active sensor node, cluster head, sink node and dead node, respectively. The green lines represent single-hop routing paths.

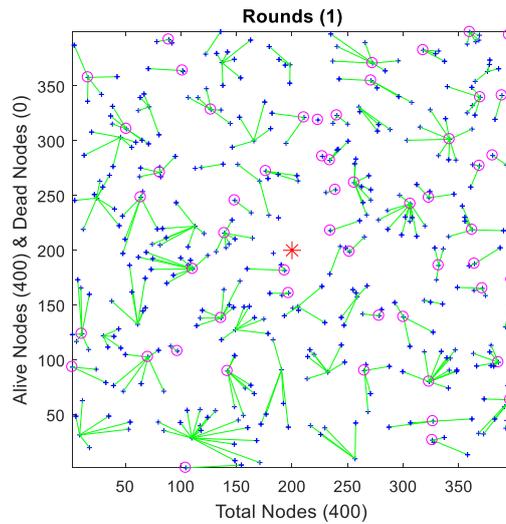


Fig. 3. 400-Node sparse random network (initial round)

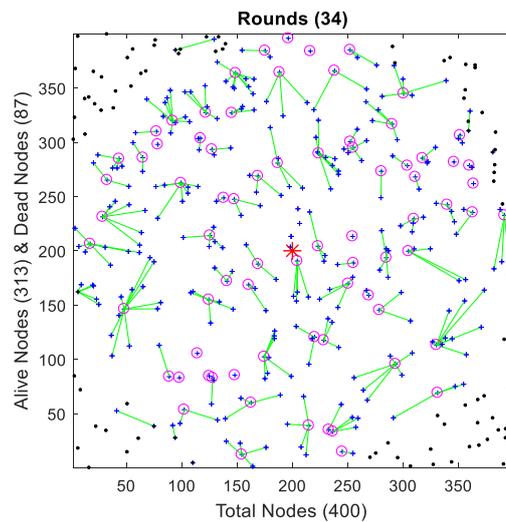


Fig. 4. 400-Node sparse random network (34th round)

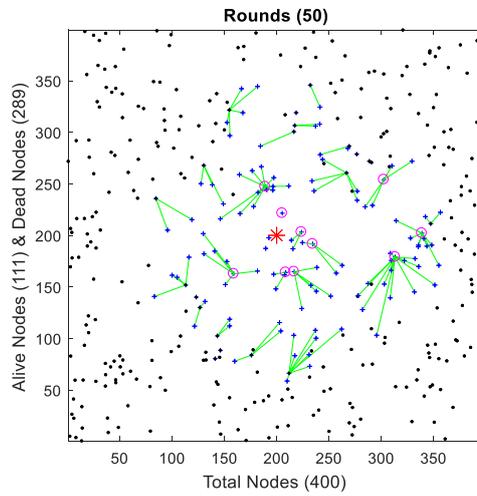


Fig. 5. 400-Node sparse random network (50th round)

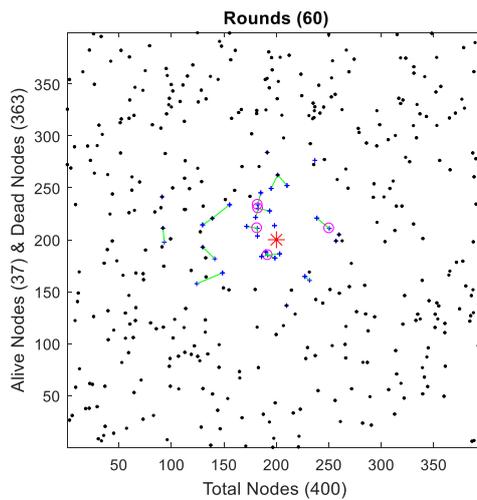


Fig. 6. 400-Node sparse random network (60th round)

From numerous simulations in general, for sparse random networks to complete all data transmission, sensor nodes near the central base station always stay the longest, while sensor nodes near the boundary edges run out of energy the fastest. An evidence is depicted by the routing process of the typical 400-node random network ($400m \times 400m$). From the initial simulation, it takes 68 rounds to reach the final stage so as to complete all data transmission during the lifespan of WSNs. Subsequent simulations are also conducted in order to observe the network dynamic patterns after 34 rounds, 50 rounds, and 60 rounds, respectively. The simulation results are shown in Figs. 3-6.

Simulation results for the diverse scalability cases are also obtained starting from the 4-node sparse random network to 1024-node sparse random network. The actual counts of final rounds, lifespans of the first active node and lifespans of the last active node are collected and plotted in 3 sets of curves of Fig. 7. The mismatch between two separate lifespan curves of the first active node and last active node in Fig. 7 is in fact relevant to the load imbalance of the sparse random network.

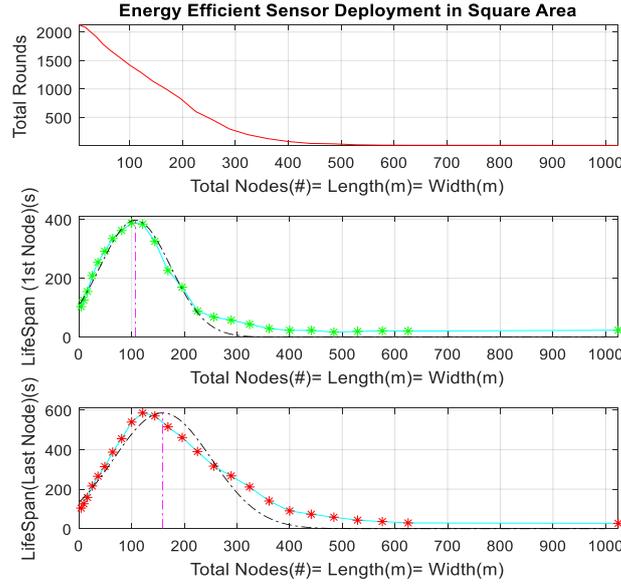


Fig. 7. Sparse random network lifespan analysis curve

It is clearly indicated from the simulations of the sparse random networks that the actual count of the final round decreases monotonically when the total count of sensor nodes increases, similar to an exponential curve. For sparse random networks, the life expectancy curves of both the first active node and the last active node exhibit the patterns of Gaussian distribution function simply described as (6), where μ acts as the expected value and σ^2 acts as the variance of the Gaussian function.

$$g(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (6)$$

By introducing the nonlinear Least Squares curve fitting, it is easy to approximate the expected value corresponding to the maximal lifespan and the variance of the Gaussian distribution curve. The maximal lifespan of the first active node occurs when 107 sensor nodes are deployed in the sparse random network, while maximal lifespan of the last active node occurs when 158 sensor nodes are deployed in the

sparse random network. Therefore it is suggested that 100-node to 160-node sparse random network should be selected to maximize the lifespan of WSNs.

5 Dense sensor node deployment

For all dense sensor node deployment in this study, the total count of sensor nodes is equivalent to the product of length (m) and width (m) of WSNs. It is shown in general that for the dense sensor network to complete all data transmission, those sensor nodes near the central base station dissipate all energy the fastest, while sensor nodes near the boundary edges will stay the longest. This result is opposite to that of sparse sensor random network. The evidence can be shown by the routing process of a 400-node dense random network ($20m \times 20m$). Based on its initial simulation, it takes more than 1300 rounds to complete all data transmission during its lifespan. Other simulations are also conducted so as to observe the network patterns after 800 rounds, 850 rounds, and 900 rounds. The simulation results are shown in Figs. 8-12.

It is clearly indicated from the dense network simulations that the maximal round occurred within network life expectancy also decreases monotonically when the total count of sensor nodes increases, similar to an exponential curve (Fig. 13). In Fig. 13, for dense random networks, the life expectancy curves of both the first active node and the last active node are however significantly different from those sparse random networks. Instead both lifespan curves increase monotonically when the total count of sensor nodes increases. On the other hand, perfect match of these two curves will theoretically represent the ideal energy distribution case across entire dense random network. Similar to the sparse random networks, the mismatch between two lifespan curves of the first active node and last active node, however, could be regarded as the measure of the load imbalance in dense random networks as well.

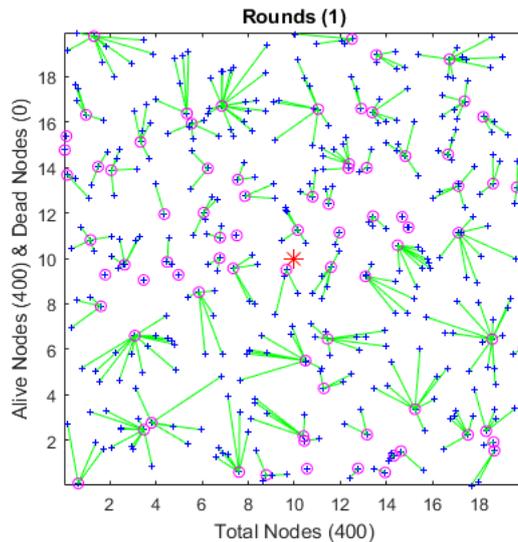


Fig. 8. 400-Node dense random network (initial round)

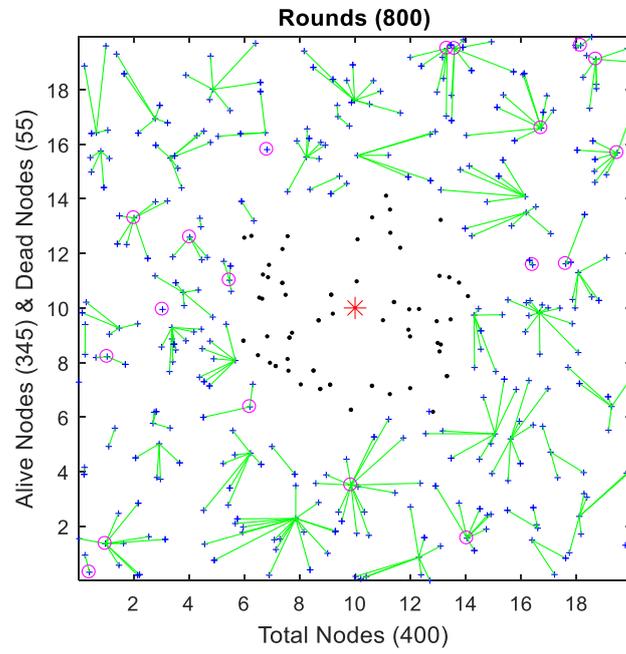


Fig. 9. 400-Node dense random network (800th round)

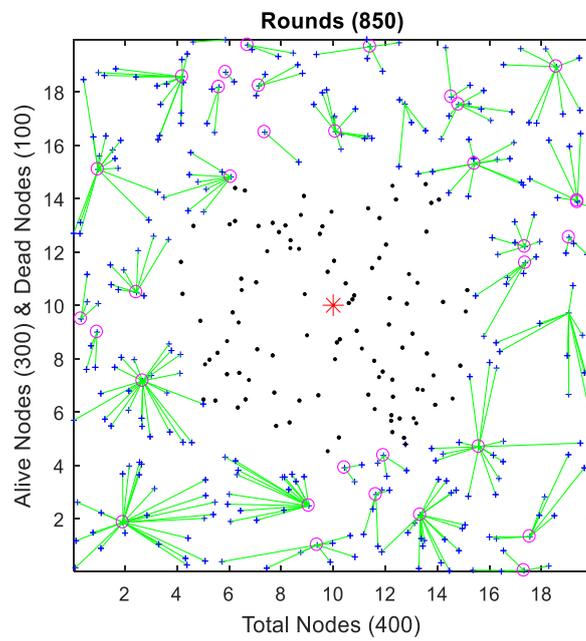


Fig. 10. 400-Node dense random network (850th round)

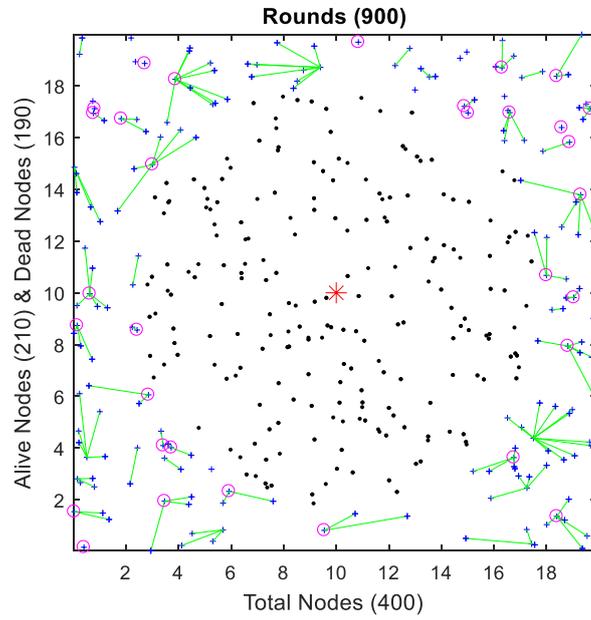


Fig. 11. 400-Node dense random network (900th round)

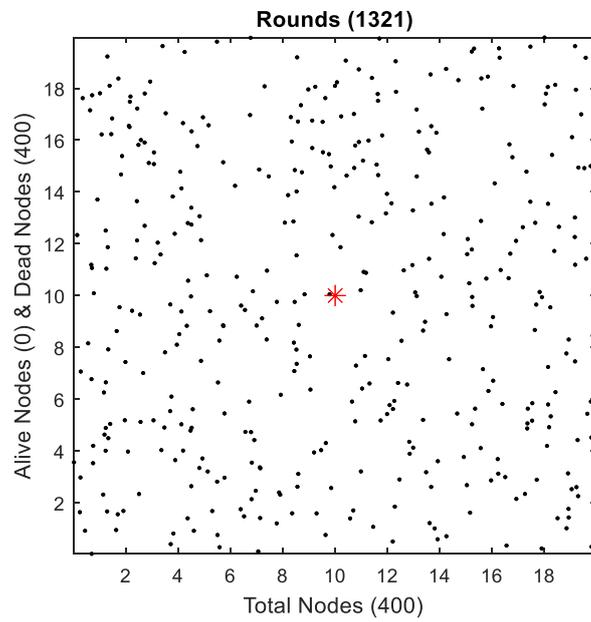


Fig. 12. 400-Node dense random network (final round)

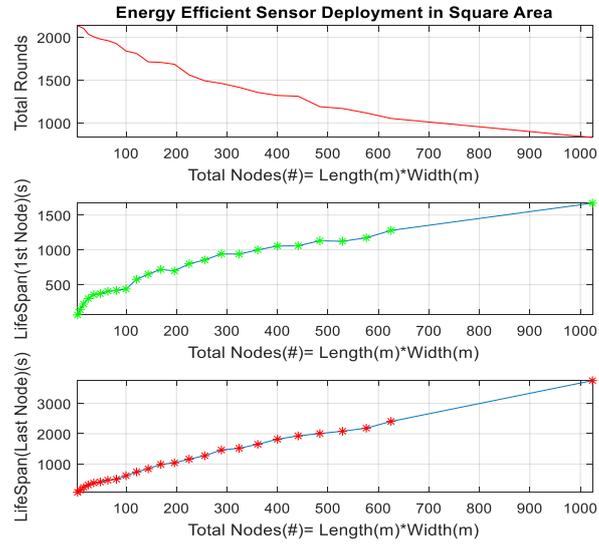


Fig. 13. Dense random network lifespan analysis curve

This discovery has also been supported by several other case studies such as on the 625-node dense random network ($25m \times 25m$). The corresponding outcomes at (600th, 700th and final) rounds are shown in Figs. 14-16.

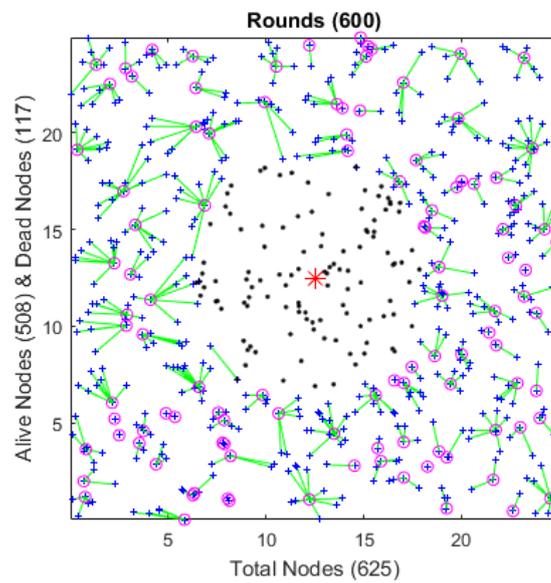


Fig. 14. 625-Node dense random network (600th round)

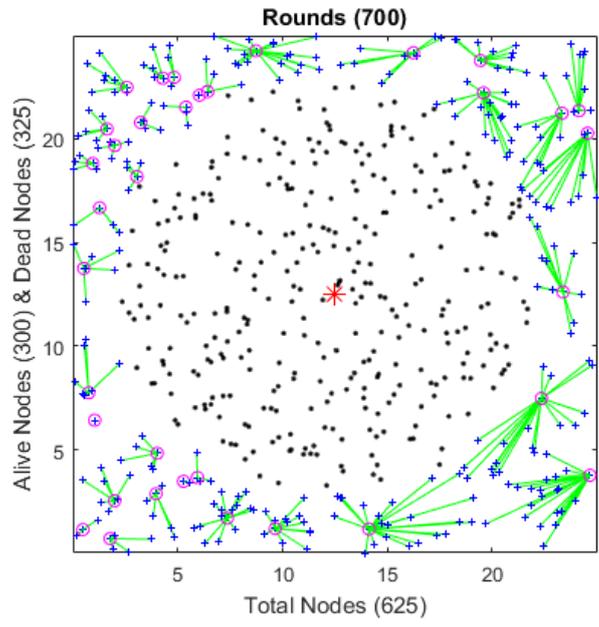


Fig. 15. 625-Node dense random network (700th round)

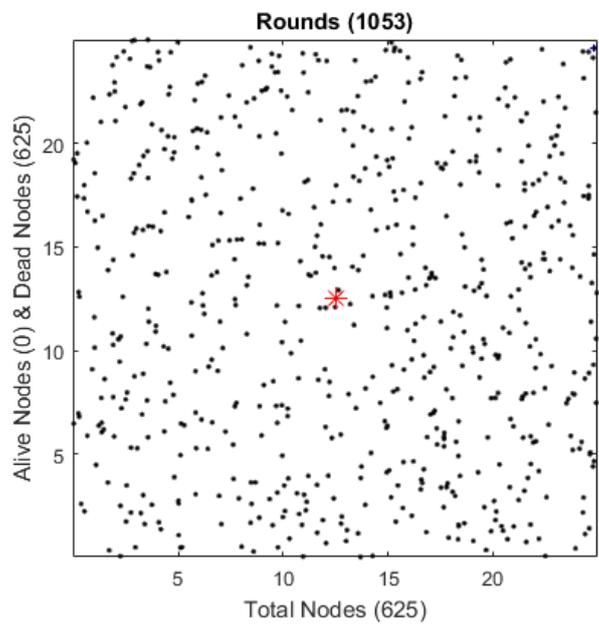


Fig. 16. 625-Node dense random network (final round)

Based on the relative slope flatness and mismatch between two curves (1st node and last node) in Fig. 13, it is suggested that actual size of a dense random network should be between 400-node network ($20m \times 20m$) and 625-node network ($25m \times 25m$) from this preliminary study.

6 Conclusion

The role of scalability and density of sensor node deployment in the WSNs lifespan has been examined, where energy-efficient hierarchical LEACH protocol is applied in order to compare the lifespan of the sensor network in diverse cases with various node densities and network diameters. After a number of initial rounds through LEACH, the residual energy of all neighboring nodes must be computed and sorted in order to determine the cluster heads in the future around. Characteristics of both sparse sensor node deployment and dense sensor node deployment are analyzed in detail, where reasonable degree of scalability via numerical simulations has been located for two cases. It is also observed that sensor nodes near the central base station last the longest for sparse sensor node deployment, while those sensor nodes near boundary edges last the longest for dense sensor node deployment. The preliminary simulation results are all based on single-hop routing, however, the proposed protocol can be easily expanded to multi-hop routing. Meanwhile, when the packet loss, end-to-end delay, interference, latency and security are all taken into account, advanced robust topological control is necessary to achieve reliable power control of wireless sensor networks against the potential load imbalance so as to accomplish the longest lifespan.

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