Near-Optimal Lifetime Maximization in Energy-Efficient Wireless Sensor Random Networks via Scalability and Density Synthesis Based Energy Load Balancing

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Abstract: - Both dense and sparse Wireless Sensor Networks (WSNs) are broadly applied due to the rapid development of control, computation and communication technologies. Impact of either scalability or density on the lifetime of WSNs has however seldom been analyzed and synthesized, which depends on sensor node deployment optimization. Scalability is one of the leading factors in enhancing connectivity, mobility, reliability and coverage range of WSNs, which in turn directly affects the WSNs lifetime defined in terms of either the first energy-exhausted sensor node or last energy-exhausted sensor node of WSNs. In order to minimize power consumption and maximize the WSN lifetime, the energy-efficient WSNs protocol is proposed to examine the impact of both scalability and density on WSNs lifetime. In practical implementation of WSNs, transceiver circuit energy and path transmission energy are both major parts of energy dissipation, thus it has never been proved whether the single-hop routing or multi-hop routing would always be superior to another. Mostly multi-hop routing is more applicable to WSNs with relatively small radio transceiver power within large diameter coverage range. Instead single-hop routing is more applicable to WSNs with relatively large radio transceiver power within small diameter coverage range. For the matter of simplicity, the single-hop routing is selected for WSNs characteristic analysis and synthesis based on multiple scalability based and density based topological deployment. Via comprehensive numerical case analysis, the practical near-optimal solution to maximize the WSNs lifetime has been reached. This approach can be easily expanded to multi-hop routing cases in WSNs.

Key-Words: - Wireless Sensor Networks, Scalability, Density, Lifetime, Adaptive Clustering, Energy Load Balancing, Hierarchical Clustering, Dense Deployment, Sparse Deployment

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1 Introduction

Wireless sensor networks provide flexibility for the sensor nodes to communicate with each other. There are numerous spatially placed sensor nodes in WSNs, which turn out to be small battery powered autonomous devices enabling data processing and short-range radio communication with seamless connectivity. Wireless channels are widely used for transmitting and receiving data among sensor nodes. The network densities of WSNs differ significantly ranging from sparse to dense deployment. Integration of communication, control, computing, middleware, hardware, and sensing technologies makes it possible to design compact scale and low energy dissipation devices, which also supports the deployment of wireless networks. WSNs are subject to limitation of battery power, operating power, bandwidth and memory storage as well as the deployment scale. The dense network enhances the chance of signal detection. For dense deployment of WSNs such as the wireless cellular networks, information redundancy on broadcasting needs to be taken into account against the hostile environment as well [1-2]. In fact both WSN random deployment and deterministic deployment can be implemented, but the former is more practical and more applicable for large or hostile areas than the latter.

The popular low energy adaptive clustering hierarchy (LEACH) is proposed to evaluate the performance with respect to WSNs lifetime, quality and latency. It enables the distributed processing to reduce energy dissipation via cluster self-organization, adaptive clustering, cluster head rotating, balanced energy load distribution and application-specific data aggregation. In reality though, practical node heterogeneity and cluster head load imbalance can sacrifice the network lifetime. Thus 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 subsequent rounds, so as to transmit the data to central base stations [3]. The basic LEACH protocol can be modified from various aspects for lifetime expansion. The near-optimal chain-based protocol is

adopted to optimize the sensor energy efficiency via power-efficient information gathering. Each sensor node only communicates with the nearest neighbor and then the data are transmitted to the base station in sequence. The energy consumption each round is reduced accordingly [4]. The multi-hop LEACH protocol via clustering is also examined which could outperform the single-hop LEACH protocol by means of energy consumption, lifetime and stability. Heterogeneous nodes are used for data transmission through optimal paths from cluster heads (CHs) to the base station (BS) [5]. An energy-efficient clustering protocol is presented as well for the heterogeneous WSNs using data aggregation. Reelection of cluster heads and scheduling of routing paths for data transmission are dependent on the residual energy of sensor nodes [6].

The balanced data aggregation scheme has been applied via clustering. The sensor network is split into numerous rectangular grids. One cluster head per grid is elected for load balance among sensor nodes and for sensor node management in WSNs [7]. An energy-efficient reliable data aggregation scheme is also introduced with clustering. Cluster head is elected on a basis of residue energy and transmission distance from the node to coordinate node. Data aggregation is conducted next to transmit data to the base station [8]. For cellular networks, direct sink access is applied to mobile data collection via clustering. Clustering and data correlation make it possible for cluster heads to operate under small overhead and medium access control. Across a broad range of parameters, latency and energy consumption decrease dramatically with robustness [9]. The lifespan of WSNs highly depends on the energy efficiency. Data aggregation is critical for redundancy reduction and transmission cost reduction. There exists a tradeoff among reliability, energy usage and latency. Dynamic routing is helpful for performance enhancement via adaptive clustering. The generalized Ant Colony Optimization (ACO) is proposed for lifespan expansion of sensor nodes with energy constraints. The residual energy of each sensor node is computed, in order to dynamically approximate probabilities for optimal channel selection [10]. The music-based harmony search optimization is introduced and practiced in real time for WSNs. It intends to optimize energy distribution by minimizing intra-cluster distances between cluster heads and other nodes so as to prolong the lifespan. This protocol manifests better performance than LEACH protocol and fuzzy C-means clustering scheme [11]. The non-virtualized WSNs suffer from high expense in deployment and maintenance due to embedded applications in sensor nodes. The task assignment in the virtualized WSNs for energy consumption minimization with specified deadlines is formulated as an Integer Linear Programming problem. It results in close-to-optimal solutions with short execution time which also outperforms the existing benchmarks with respect to the successful task execution rate [12]. 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 WSNs lifetime in this preliminary study. The interesting outcomes simply inspire the leading contributor of corresponding research for comprehensive analysis and synthesis on this topic [13]. In fact AI techniques can be further integrated with WSNs for performance optimization. From one of existing AI schemes, every WSN has location-based nodes and target nodes. It is more challenging to locate nodes in anisotropic WSNs. The fuzzy inference system is used to optimize the distance between anchor and target nodes. The localization error is calculated under different node densities, anchor nodes, and degree of irregularity values. Fuzzy modeling provides better location estimation than classical schemes [14].

2 Energy Dissipation Model of WSNs (Wireless Sensor Networks)

WSNs encompass mini low power and low speed sensor nodes to detect, collect and transmit data via radio waves. It covers sensors, transducers, transceivers, memory, processor, power source, base station and middleware. A sensor node typically consists of four basic components such as the sensing unit, processing unit, transceiver unit and power unit. The central base station (also sink node) serves as the central point of the wireless communication networks. It acts as the gateway between WSNs and external systems. The central base station receives the aggregated data from the WSNs and then transmits data to the target destination (e.g. servers, user interfaces). The energy load balancing is always crucial in WSNs for close match between supply and demand. The flexibility in energy systems helps to adjust supply and demand for energy load balancing. To successfully transmit and receive a single packet of size K, the energy dissipation is computed as (1).

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

where $E_T(d, K)$ represents the total energy dissipation to send, transmit and receive a packet of the data size K [Bits]; E_{TR_ELE} [J/Bit] represents overhead energy of transmitter electronics (e.g.,

modulation, phase lock, filtering, digital coding); E_{DA} [J/Bit] represents the additional energy dissipated by cluster heads for data aggregation and compression, where cluster heads are in charge of receiving and collecting data from some other intra-cluster sensor nodes, then compressing, and sending the data to the base station; E_{AMP} [J/Bit] represents the radio wave propagation energy consumed in power amplifiers as being defined in (2); E_{RE_ELE} [J/Bit] represents the overhead energy of receiver electronics (e.g., digital decoding, demodulation); d [m] represents the radio propagation distance from the transmitter to receiver; ε [J/Bit*m$^{\lambda}$] represents the transmission amplifier cofactor; λ represents the path loss exponent.

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

The path loss exponent λ differs between single path and multiple path propagation. For instance, the free space channel model defines λ as 2 for single path propagation but it defines λ as 4 for multi-path propagation in the fading channel model. In practice, λ could be assigned as 4 when data transmission starts from the cluster head nodes, while λ is assigned as 2 when data transmission starts from other sensor nodes.

For an arbitrary cluster with M sensor nodes, only one sensor node serves as the cluster head (CH) each round. Then the residual energy E_{CH} of the cluster head must satisfy (3) so as to deliver the data packet successfully.

$$E_{CH} >= (M-1) \times (E_{TR_ELE} + E_{DA}) \quad (3)$$

The residual energy E_{RS} of each sensor node is simply the difference between initial energy E_{INI} and its own dissipated energy E_T for the actual node, as expressed 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 remaining at the idle mode (inactivity). The residual energy of cluster head drops quickly because the CHs consume more energy than other sensor nodes which exhaust very soon. To extend the lifetime, rotation of CHs via reelection could be conducted each round to avoid draining the energy so soon. In this case, all sensor nodes in a cluster will share the responsibility of CHs to partially compensate for load imbalance of WSNs. For the LEACH protocol, energy should be distributed evenly, thus all nodes are supposed to serve as cluster heads via rotation in sequence. Since the entire network has been divided into a number of clusters covering randomly distributed active nodes and dead nodes as well as randomly selected initial CHs, load imbalance among all clusters and CHs could shorten the network lifetime. Thus energy-efficient dynamic routing scheme is necessary to be modified in order to substitute the classical LEACH protocol. The optimality on energy efficiency is however too hard to reach due to numerous factors against diversified complex harsh environments. Analytical optimal number of clusters and optimal number of hops are never solved uniquely. The focus of this research is to explore the near-optimal solution to maximize the WSN lifetime in terms of scalability-based and density-based topology optimization via energy-efficient dynamic routing.

3 Energy-Efficient Dynamic Routing of WSNs

The readily applicable energy-efficient routing protocol has been proposed. In the initial 1/p rounds, dynamic routing of WSNs follows the classical hierarchical LEACH protocol. It involves the tradeoff between low energy dissipation and latency. Clustering is beneficial to energy load balancing for intra-cluster communication. Because the cluster heads (CHs) generally consume more energy than other sensor nodes, rotating between CH nodes and non-CH nodes in a cluster could be solution. CHs should be randomly selected beforehand, which are in charge of data aggregation and transmission. For inter-cluster communication instead, initial clustering and sensor node deployment are important to split all sensor nodes into groups and to place nodes in predetermined locations, which are dependent on the scalability and density of WSNs. WSNs always operate under energy-constrained environments because WSNs are designed for low speed communication applications. The stochastic scheme (5) is used to create a threshold in order to assign the CHs. For each sensor node, a random number is generated ranging from 0 to 1. If it is less than the specified threshold, then it turns out to be the CH of that round, otherwise it serves as a cluster member under certain cluster head which can provide it with the maximal signal strength. This threshold θ is computed via (5) as below.

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

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

After 1/p rounds, the energy-efficient dynamic routing is directly applied to substitute the LEACH

protocol. In fact, the assumption of homogeneous sensor nodes during the setup phase is not feasible for those WSNs with large diameters. Most sensor networks are heterogeneous in reality. The residual energy of each sensor node will play the leading role in all 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, each non-cluster-head sensor node will join in an updated cluster whose CH provides the maximal signal strength to this non-cluster-head sensor node in the next round. The energy load imbalance problems can be improved in turn. This simple protocol scheme is operated continuously throughout the life expectancy of WSNs.

Three phases are applied in each round, i.e., cluster head election and broadcasting, cluster membership setup, and steady state data transmission. At the steady state, cluster heads will aggregate and transmit the data. Data packets can only be transmitted via active sensor nodes. Meanwhile the other sleepy nodes stay idle upon communication for concern of energy conservation. The energy dissipation model mentioned earlier will incorporate those transmitting energy, propagation path loss energy, receiving energy, aggregating and compression energy.

4 Parameter Selection in Simulations

In comparison with single-hop transmission, the multi-hop protocol requires extra hop counts where excessive overhead energy of both transmitter electronics and receiver electronics will be required. Within scope of low diameter data transmission, single-hop transmission is generally more energy efficient. For relatively large diameter data transmission, the possible high power consumption of transceiver radio operation is also in favour of single-hop transmission. Even multi-hop protocol does conserve certain amount of transmission energy, it is still subject to tradeoff among extra packet loss, additional latency, severe end-to-end delay, traffic collision, supplementary interference and exceptional load imbalance, as well as security issues. For the matter of simplicity, single hop transmission is applied in numerical simulations. Various case studies are conducted and analyzed with parameters below for purposes of additional comprehensive synthesis.

The initial energy for each sensor node is set to be 0.5J. The energy dissipation for the transmitter and receiver to send and receive a packet are assumed to be the equal, which is assumed to be 50 nJ per bit. The energy dissipation cofactor ε of the path transmitting amplifier is set to be 100pJ/bit/m^{λ}. Data aggregation and compression energy consumed by the cluster heads is set to be 5 nJ per bit. The data packet size is set to be 2000 bits. The specified percentage of CHs for all sensor nodes is fixed throughout all rounds in the simulation. The scalability of WSNs is manifested by the total quantity of sensor nodes within the 2D square network in meter, which ranges from 4 (2^2) to 1024 (2^{10}). The more practical square area is taken rather than those possible 2D circular area and 3D spherical volume to describe the random sensor network topology of WSNs.

Deployment of WSNs is simplified into two typical cases of dense sensor node deployment and sparse sensor node deployment based on the density. For dense sensor node deployment, the length and width are both rounded to the square root of total quantity of sensor nodes. For sparse sensor node deployment, the length and width are both set to be equal to the total amount of sensor nodes. The definition of WSNs lifetime is also not unique. To completely examine the lifetime characteristics of WSNs, two diverse definitions are both adopted. Firstly, it is defined as the life expectancy for the first sensor node to exhaust its energy. Secondly, it can also be defined as the life expectancy for the last sensor node to exhaust its energy. From the 4-node random network to 100-node random network, until 1000-node random network (1024), the impact of both scalability and density on the lifetime of WSNs will be observed. For single-hop transmission, the size of each cluster will be constrained by the range of radio waves. As a matter of fact, the applied single-hop protocol can be easily extended to other multiple-hop protocols of WSNs. For existing dense and sparse sensor networks mentioned in context, it is better to determine the reasonable scope of scalability and density relevant to the maximal lifetime of WSNs.

5 Dense Sensor Node Deployment

Scalability plays a critical role in WSN routing protocol design. Without a universal definition on scalability of WSNs, in this context, scalability specifies the capability of scaling up and scaling down the coverage range of WSN environment by expanding or shrinking the quantity of sensor nodes adaptable to various application requirements. The routing protocol indeed should be adaptable and scalable to the variations in the network topology. Smooth tradeoff exists between low energy

dissipation and latency. The dense network has the benefit of enhancing signal-to-noise ratio (SNR) and strengthening signal detection. On the other hand, the density of WSNs instead refers to the quantity of sensor nodes deployed per coverage area. It manifests the number of neighboring nodes and the potential data traffic of clusters. For dense sensor networks, another benefit is that the dissipated energy is at relatively low level because several shortest paths might occur from a source to a sink simultaneously.

The definition of the WSNs lifetime is not unique either. It can be defined as the time duration from the initial time until the first sensor node exhausts its energy in the network, while it can also be defined as the time duration from the initial time until the last sensor node exhausts its energy in the network. The former indicates the amount of time for WSNs to be fully operative while the latter indicates the amount of time for WSNs to be still functional. The maximal time duration is of great interest for deployed sensors with the capability of detecting or monitoring in both cases actually. To comprehensively discover the detailed information of WSNs routing process, in order to possibly optimize its lifetime, mostly the definition of the time duration from initial time until the last sensor node exhausts its energy has been adopted as the lifetime of WSNs in existing numerical simulation cases. The metrics of both scalability and density affect the overall network lifetime, resource allocation, inter-cluster and intra-cluster communications.

In this session, the impact of scalability on the lifetime of WSNs is analyzed under fixed density of sensor nodes. The quantity of sensor nodes per square area is equivalent to the product of length (L in meter) and width (W=L) of WSNs. It is regarded as the dense sensor node deployment, when compared with the sparse sensor node deployment in the next session. In Fig. 1, the patterns of initial rounds for three dense random networks deployment are shown, where the scalability varies (from 2^6 to 2^8 and 2^{10}) under the fixed density. Only the patterns of the initial round are shown, where blue "+", pink "o", red "*" and black "." represent the active sensor node, cluster head, sink node and dead node, respectively. The green lines represent single-hop routing paths. The base station or sink node serves as the central point of wireless communication in the network. It also serves as a gateway between the WSN and external systems. The sink node receives the aggregated data from the network and then forwards it to the intended destination.

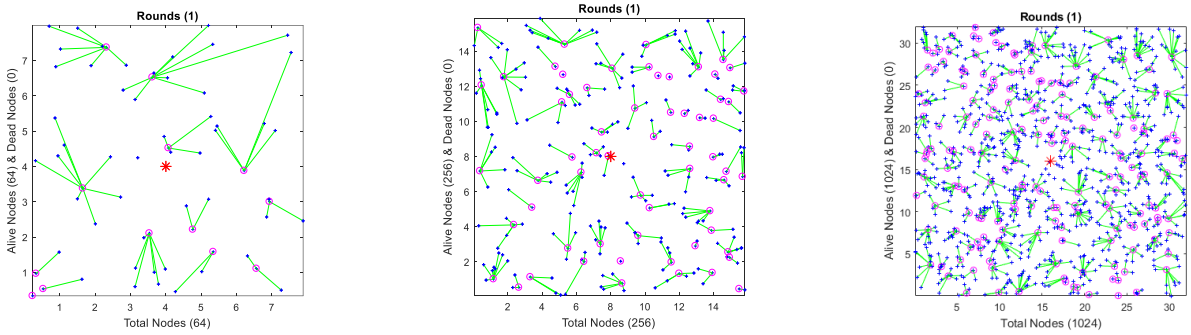

Fig. 1. Multiple Scalability Random Network Deployment with Fixed Density (Initial Round)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

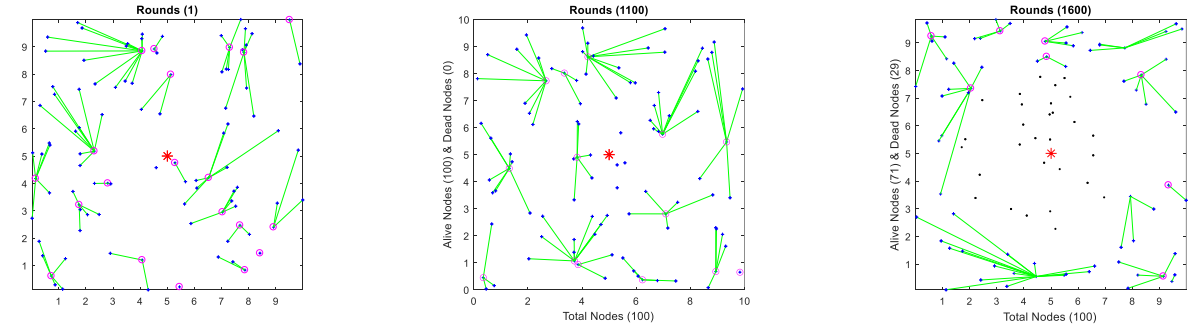

Fig. 2. 100-Node (10m×10m) Dense Random Network with Fixed Density (Initial Round, Round 1100, Round 1600)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

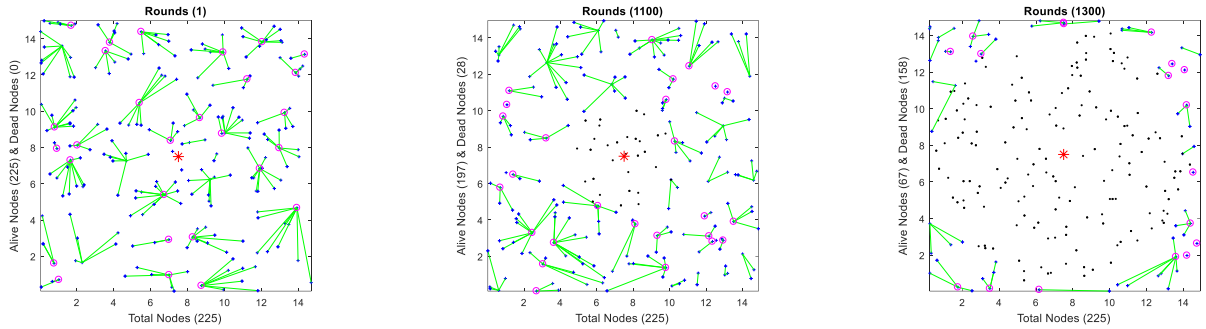

Fig. 3. 225-Node (15m×15m) Dense Random Network with Fixed Density (Initial Round, Round 1100, Round 1300)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

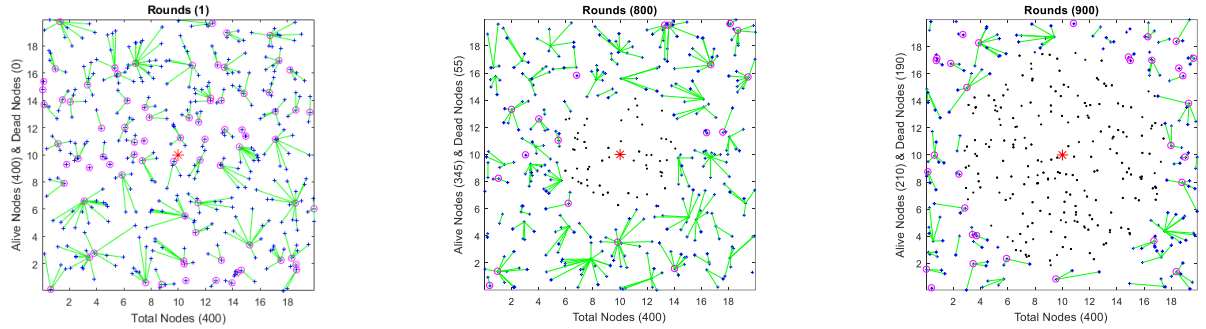

Fig. 4. 400-Node (20m×20m) Dense Random Network with Fixed Density (Initial Round, Round 800, Round 900)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

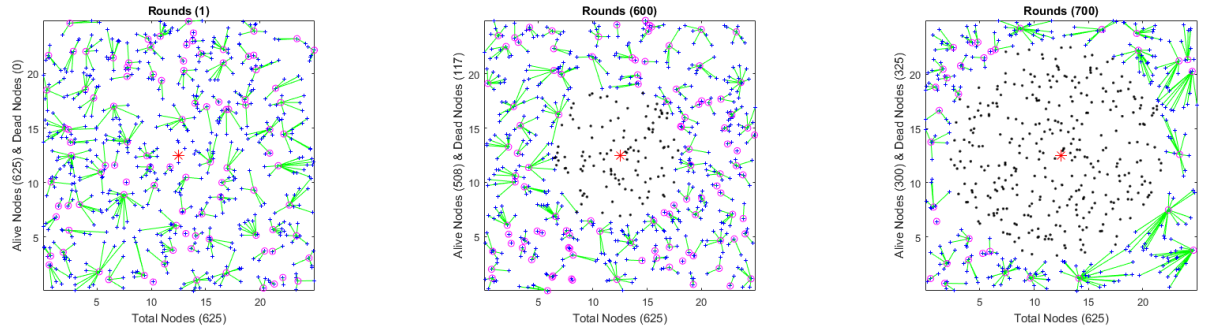

Fig. 5. 625-Node (25m×25m) Dense Random Network with Fixed Density (Initial Round, Round 600, Round 700)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

Without loss of generality, routing processes of 100-node dense random network (10m×10m), 225-node dense random network (15m×15m), 400-node dense random network (20m×20m), and 625-node dense random network (25m×25m) are selected to analyze and synthesize the lifetime characteristics of WSNs. It is demonstrated across each level of scalability that for the relevant dense sensor network to complete all data transmission, those sensor nodes near the central base station (small distance) always dissipate all energy most rapidly, while remote sensor nodes near the boundaries (large distance) dissipate all energy most slowly. The simulation results of dense sensor random networks are shown in Figs. 2-5, covering fours cases of 100-node (10m×10m), 225-node (15m×15m), 400-node (20m×20m), and 625-node(25m×25m), respectively. The actual round of each simulation has been predetermined beforehand. At the low scale with 100-node (10m×10m), the sensor network is fully operative at round 1100, while over 70% of sensor nodes are still functional at round 1600. After scaling up to 225-node (15m×15m) instead, the sensor network is no longer fully operative at round 1100, with less than 90% of sensor nodes still functional. Meanwhile it has less than 30% of sensor nodes functional at round 1300. The maximal round drops significantly after further scaling up to 400-node (20m×20m), 625-node (25m×25m), respectively. For the case of 400-node (20m×20m), the sensor network has less than 90% of sensor nodes functional at round 800 while about 50% of sensor nodes are functional at round 900. For the case of 625-node (25m×25m) instead, the sensor network has about 80% of sensor nodes functional at round 600, while less than 50% of sensor nodes

are functional at round 700. On the other hand, when the random network is scaled up from the 100-node to 225-node, 400-node and 625-node, the actual round near final stages of WSNs lifetime drops remarkably from 1600 to 1300, 900 and 700 or so. Similar results also occur at the middle stage of the WSNs lifetime when it is scaled up from 100-node to 225-node, 400-node and 625-node. The total round within the WSNs lifetime changes in the opposite way when a random network is scaled up.

6 Sparse Sensor Node Deployment

For all sparse sensor node deployment, the actual quantity of sensor nodes per square area is equivalent to its length (L) or width (W=L) of WSNs. Once again, blue "+", pink "o", red "*" and black "." represent the active sensor node, cluster head, sink node and dead node, respectively. The green lines represent single-hop routing paths.

Without loss of generality, routing processes of 100-node sparse random network (100m×100m), 225-node dense random network (225m×225m), and 400-node dense random network (400m×400m) are selected to analyze and synthesize the impact of scalability and density on WSNs lifetime. The quantity of sensor nodes in the sparse sensor network is thus equal to the square root of the total area rather than the total area as being adopted in the dense sensor network session. The network density is no longer a fixed constant instead but inversely proportional to the quantity of sensor nodes. The more the sensor nodes, the less the network density. It is demonstrated across diverse levels of scalability that for the sparse sensor network to complete all data transmission, remote sensor nodes near the boundaries (large distance) dissipate all energy most rapidly, while those sensor nodes near the central base station (small distance) always dissipate all energy most slowly.

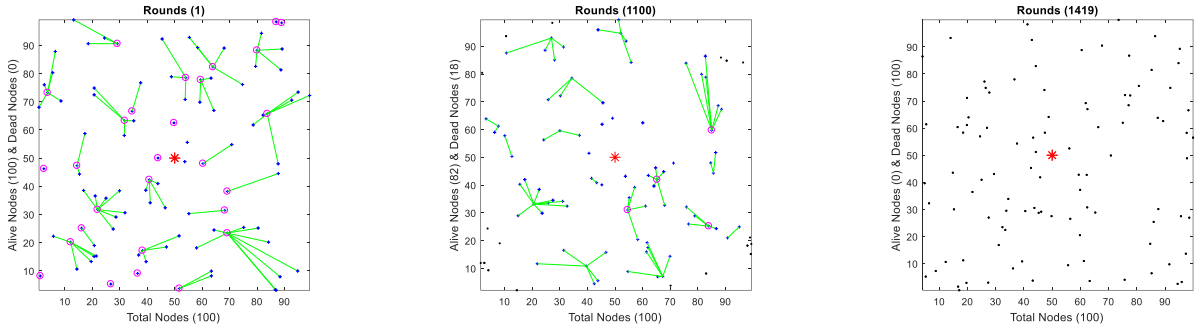

Fig. 6. 100-Node (100m×100m) Sparse Random Network (Initial Round, Round 1100, Final Round)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

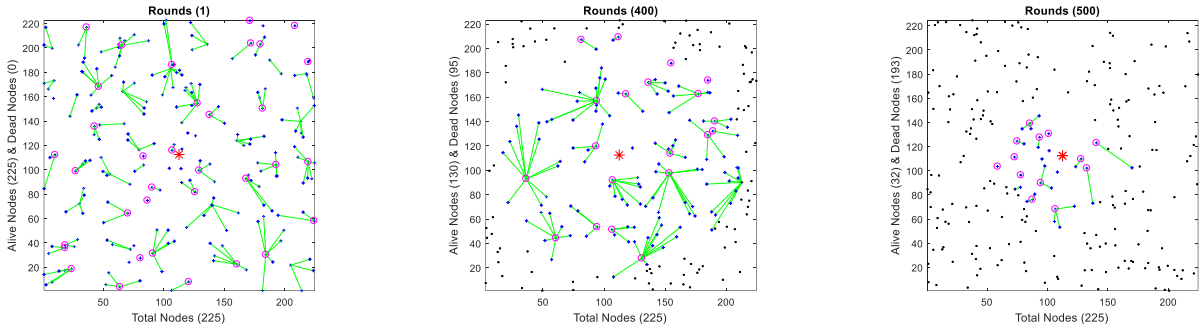

Fig. 7. 225-Node (225m×225m) Sparse Random Network (Initial Round, Round 400, Round 500)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

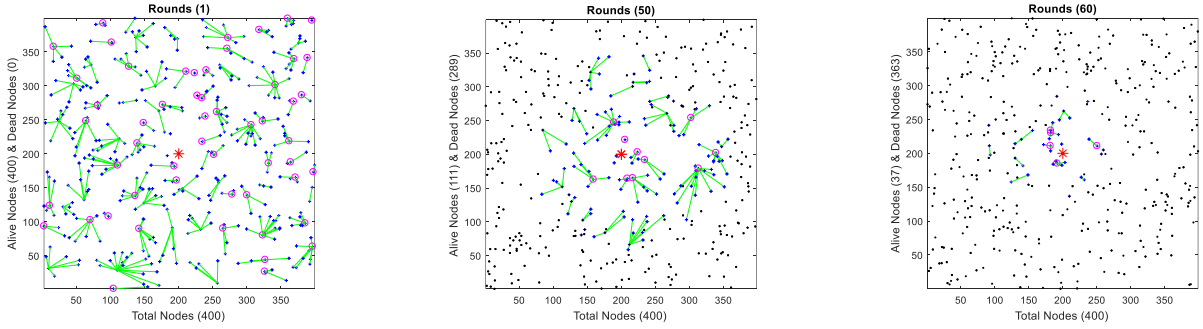

Fig. 8. 400-Node (400m×400m) Sparse Random Network (Initial Round, Round 50, Round 60)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

The simulation results of sparse sensor random network are shown in Figs. 6-8, covering cases of 100-node (100m×100m), 225-node (225m×225m), 400-node (400m×400m), respectively. At the low scale with 100-node (100m×100m), over 80% of sensor nodes of the sensor network are still functional but not fully operative at round 1100, while the final round occurs right after round 1400. After scaling up to 225-node (225m×225m), the sensor network has less than 60% of sensor nodes functional at round 400, while less than 15% of sensor nodes are still functional at round 500. The total round drops significantly when further scaling up to 400-node (400m×400m), the sensor network has less than 30% of sensor nodes functional at round 50, while less than 10% of sensor nodes are functional at round 60. For cases of 625-node (25m×25m), 900-node (900m×900m), 1024-node (1024m×1024m), and so on, due to oversize and quick functionality loss, it is not necessary to show additional simulation results. When a sparse sensor random network is scaled up from 100-node to 225-node and 400-node, the total round near final stages of WSNs lifetime drops remarkably from above 1000 down to below 100. Similar results also occur in the middle stages of the WSNs lifetime when scaling up from 100-node to 225-node, and 400-node. The total round within the lifetime changes in the opposite way when the random network has been scaled up.

7 Load Imbalance in Dense and Sparse Sensor Node Deployment

Simulation results for diverse scalability cases are generated starting from the 4-node (2^2) to 1024-node (2^{10}) dense random network. Based on simulations of dense sensor network (Fig. 9), the maximal total round within network life expectancy decreases monotonically when the quantity of sensor nodes increases, identical to an exponential curve. In fact for dense random networks, the life expectancy curves of both the first energy-exhausted node and last energy-exhausted node are completely different from those in corresponding sparse random networks. 2 lifetime curves increase monotonically when the total quantity of sensor nodes increases. Essentially perfect match of these two curves would indicate the ideal balanced energy distribution across entire dense random network. The actual mismatch between two lifetime curves of the first exhausted node and last exhausted node can be viewed as the measure for load imbalance in the dense random networks. Based on the steepness of the slope of two curves and mismatch between two curves, it is suggested that the size should be between the 400-node dense random network and 625-node dense random network to maximize the lifetime of WSNs whenever the dense WSNs are deployed.

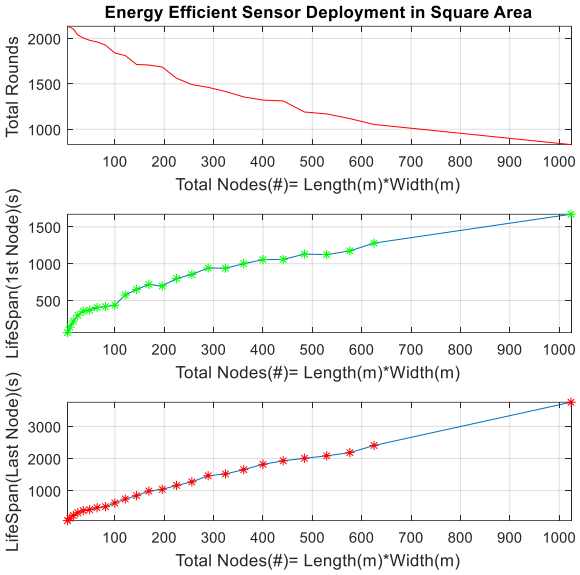

Fig. 9. Dense Random Network Lifetime Analysis Curve

Similarly some numerical simulations on diverse scalability cases are also conducted starting from the 4-node (2^2) sparse random network to 1024-node (2^{10}) sparse random network. The corresponding maximal total round, lifetime of the first exhausted node and lifetime of the last exhausted node are collected and plotted in Fig. 10. Following the dense random network cases, the mismatch between 2 lifetime curves of the first exhausted node and last exhausted node is actually relevant to the load imbalance of the sparse random network. From simulation results of the sparse random networks, it is observed that the maximal total round decreases monotonically when the quantity of sensor nodes increases, identical to an exponential curve again. For the sparse random network however, the life expectancy curves of both the first exhausted node and the last exhausted node exhibit the pattern of the Gaussian distribution which is expressed as (6), where μ is the expected value and σ^2 is the variance of the Gaussian function.

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

After the nonlinear least squares curve fitting is applied, it is easy to approximate the mathematical expectation relevant to the maximal lifetime and variance of the Gaussian distribution curve. The maximal lifetime of the first exhausted node occurs

when about 100 sensor nodes are deployed in the network, while the maximal lifetime of the last exhausted node occurs when about 160 sensor nodes are deployed in the sparse random network. Therefore, it is suggested that the quantity of 100-node to 160-node sparse random network should be selected to maximize the lifetime of WSNs if sparse WSNs are selected.

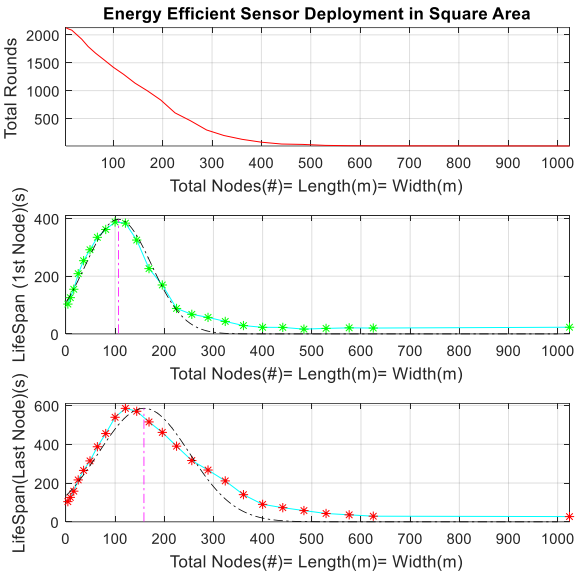

Fig. 10. Sparse Random Network Lifetime Analysis Curve

Load imbalance occurs in the routing processes of both dense and sparse sensor node deployment being defined in this research, but network traffic distribution and energy dissipation sequence are completely different between dense and sparse deployment. For dense sensor networks, those sensor nodes near the central base station always dissipate all energy most rapidly, while remote sensor nodes near the boundaries dissipate all energy most slowly. Conversely, for sparse sensor networks, those sensor nodes near the central base station always dissipate all energy most slowly, while remote sensor nodes near boundaries dissipate all energy most rapidly. For the practical concern of energy load balancing, there should be a unique topological combination of scalability and density that is relevant to the optimal energy load balancing. Given the length size of a square area L (m) and total quantity of sensor nodes within the area N, then neither the dense random network ($N=L^2$) nor the sparse random network ($N=L$) is the best option of sensor node deployment. Instead, $L< N<L^2$ is the feasible range of the optimal solution on lifetime maximization. Assume N* is the optimal number of sensor nodes and $N^*=L^{\alpha}$ where $1<\alpha<2$, then the best sensor node deployment for energy balancing in terms of scalability and density is converted into an optimization problem to locate the exact α ($1<\alpha<2$).

On the other hand, let us fix the WSN scalability (e.g. 40m×40m) while adjust the network density this time, aiming to determine the near optimal baseline network deployment with the maximal WSNs lifetime. The inequality above must always be satisfied for all experimental random networks. Now comparisons among cases of 100-node, 80-node, and 50-node are made. After 1500 rounds (100-node), 1600 rounds (80-node), and 1760 rounds (50-node), 9% sensor nodes near the base station, 15% sensor nodes near the base station and 10% sensor nodes close to the area boundary, have completely dissipated the energy, respectively, depicting totally diverse directions of sensing function loss (towards vs away from a sink node or central station) when the density decreases in order (Fig. 11). In this case, under the equal level of scalability, to balance between outward and inward directions of the sensing function loss, the near optimal baseline sensor node deployment should be made at another intermediate density level which is capable of enhancing energy load balancing. Thus 60-node deployment is applied for synthesizing the detail progress occurred within one individual numerical simulation exclusively (Fig. 12), rather than analyzing merely the prevailing tendency. In particular, the topologies of sensor deployment at rounds 1730, 1735, 1740, 1745, 1750, and 1755 from one simulation have been listed together next. There is no longer priority difference between the sensor nodes located next to either minimal or maximal distance from the central station with respect to the sequence of energy consumption, which gives rise to near-optimal energy load balancing. For instance, it is noticed that at the round 1735, 50% of sensor nodes are alive and 50% of sensor nodes are out of service, while exhausted sensor nodes are evenly distributed everywhere (e.g. close to base station and close to boundary). Energy imbalance has been avoided in this case. Due to load balancing, it is also observed that it only takes merely 20 rounds (1735 to 1755) for WSNs to exhaust all remaining 50% of sensor nodes this time rather than thousands or hundreds of rounds in previous case studies. Those sensor nodes almost work together from the initial stage to final stage simultaneously. When all sensor nodes of WSNs exhaust the energy completely at the same time, it turns out to be the ideal case to optimize the WSNs lifetime and energy efficiency.

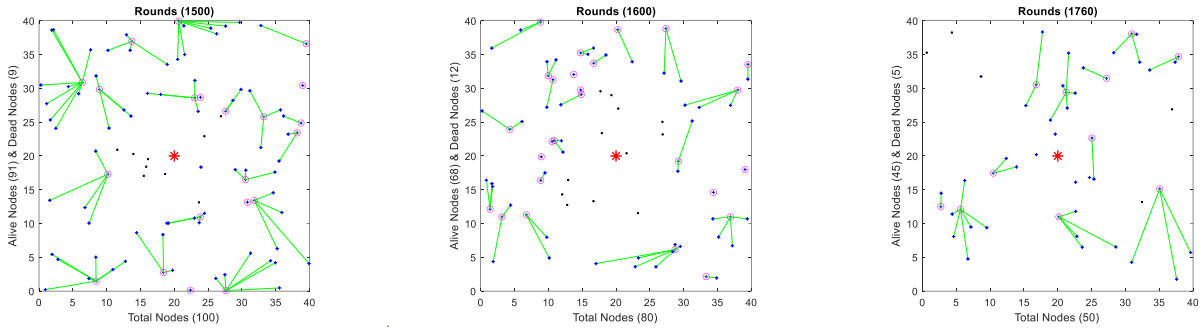

Fig. 11. Random Network Lifetime Analysis Fixed Scalability (40m×40m)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

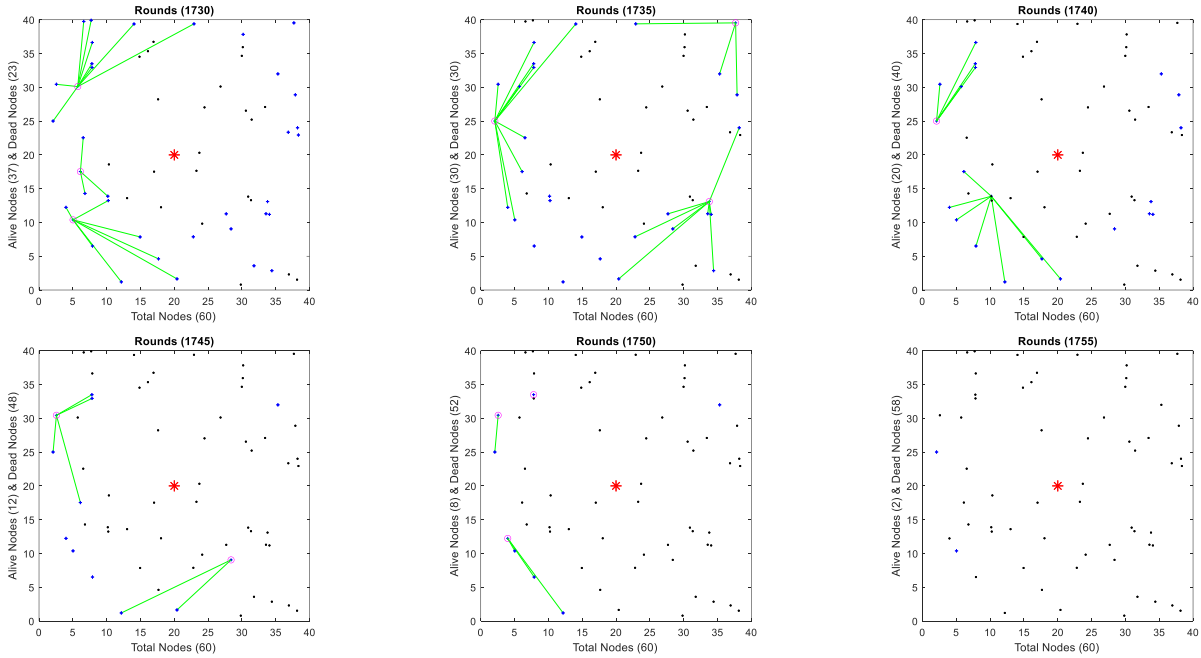

Fig. 12. Lifestime Synthesis of Near-Optimal Sensor Node Deployment at Rounds 1730, 1735, 1740, 1745, 1750, and 1755
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

Load imbalance in WSNs results from various factors, including the fixed transmission range, unbalanced sensor node distribution as well as direct source to sink transmission, and so on. All these factors have negative effects on the WSN lifetime. This research has reached the practical near-optimal solution for lifetime expansion via analysis and synthesis on the impact of scalability and density. Real world engineering applications of the WSNs could be extremely complicated, it is a challenging issue on how to reach the exact analytical solution for various WSNs lifetime optimization issues.

8 Future Work

Being a challenging research direction, integration of artificial intelligence with WSN routing is also one of the most promising and inspiring topics for advancing scientific research in WSN fields. It has the potential to enhance the efficiency, connectivity, mobility, reliability, productivity, and sustainability of WSNs. It will be beneficial to optimization issues on the WSN scale, node density and coverage scope. Numerous AI techniques are feasible to be adopted, such as the fuzzy logic systems, artificial neural networks, hybrid fuzzy neural networks, genetic algorithms, particle swarm optimization, ant colony optimization, Markov chain Monte Carlo, principal component analysis, nonlinear component analysis, independent component analysis, support vector machine, fuzzy C-means clustering, and K-nearest neighbors algorithm. These AI techniques have been successfully implemented across the author's other research areas with sole or first authorships in IEEE publications, specifically, automotive control, signal and image processing, biomedical characterization, and so on (e.g. [15]). It is pretty reasonable to expand those applications to WSN research areas.

9 Conclusions

This research focuses on near-optimal lifetime maximization of WSNs with respect to roles of scalability and density in sensor node deployment. The enhanced energy-efficient LEACH protocol is introduced so as to make comparisons on the WSNs lifetime across numerous sensor node deployment cases under diverse coverage diameters and sensor node density. Certain number of initial rounds are conducted via LEACH. Then the residual energy of all neighboring nodes will be calculated and sorted to choose cluster heads in all the subsequent rounds. Under multiple levels of scalability, the WSNs lifetime characteristics of both dense and sparse sensor node deployment are thoroughly analyzed followed by comprehensive synthesis. Interesting results are observed based on a variety of numerical simulations. In fact the sensor nodes near the base station always last the longest for sparse sensor node deployment, while sensor nodes near the base station last the shortest for the dense sensor node deployment. The optimal energy load balancing can be actually made via neither dense deployment nor sparse deployment but intermediate deployment between dense and sparse. Practical sensor node deployment strategy is obtained to reach the near-optimal energy load balancing for expanding WSNs lifetime. This work is based on single-hop routing, but the proposed protocol could be easily extended to multi-hop routing. When the packet loss, end-to-end delay, interference, latency and security are also taken into account, advanced robust topological control is necessary to achieve reliable energy load balancing for maximal lifetime of WSNs.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The author contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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Attachment List of Large Size Figures:

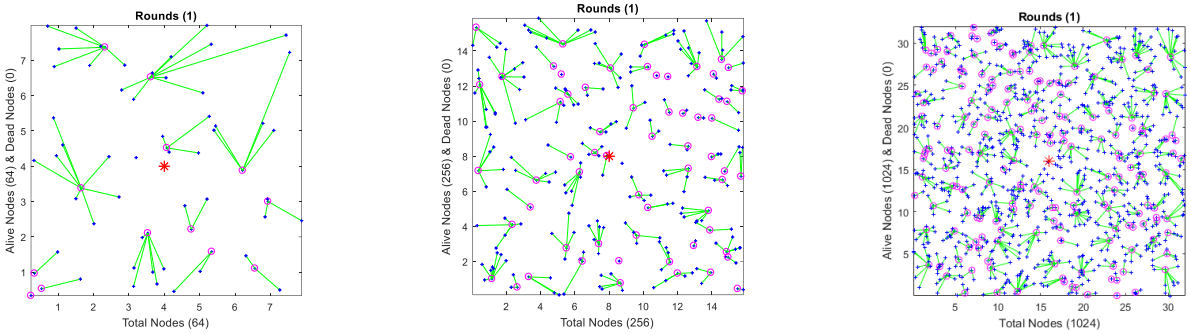

Fig. 1. Multiple Scalability Random Network Deployment with Fixed Density (Initial Round)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

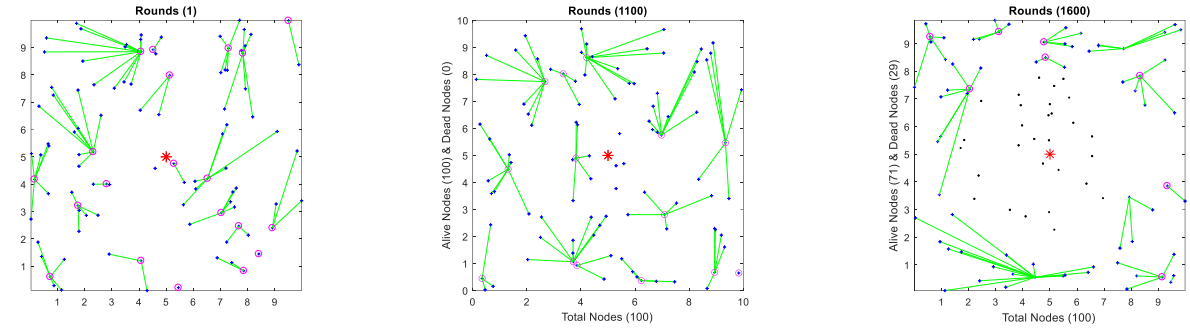

Fig. 2. 100-Node (10m×10m) Dense Random Network with Fixed Density (Initial Round, Round 1100, Round 1600)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

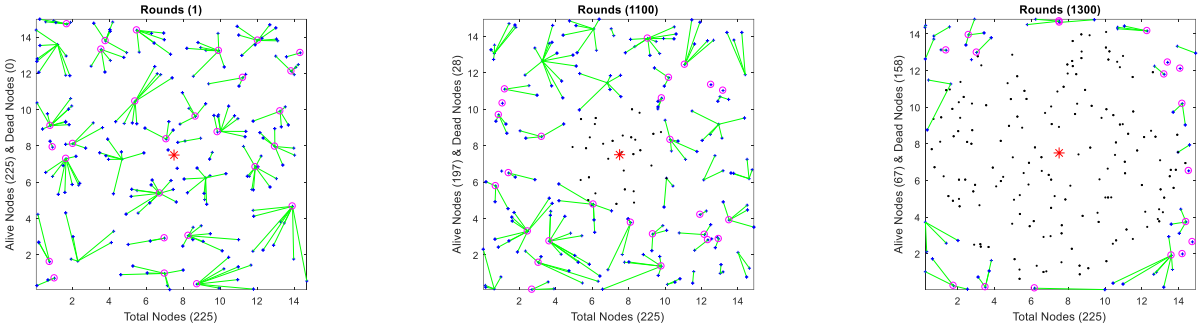

Fig. 3. 225-Node (15m×15m) Dense Random Network with Fixed Density (Initial Round, Round 1100, Round 1300)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

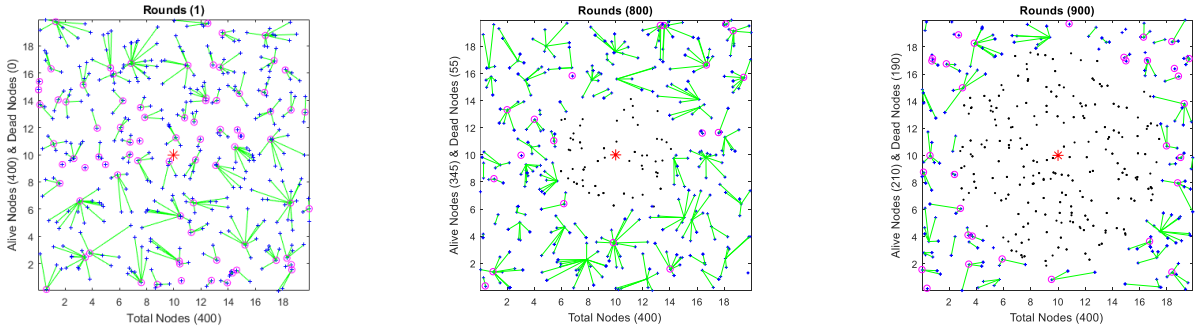

Fig. 4. 400-Node (20m×20m) Dense Random Network with Fixed Density (Initial Round, Round 800, Round 900)
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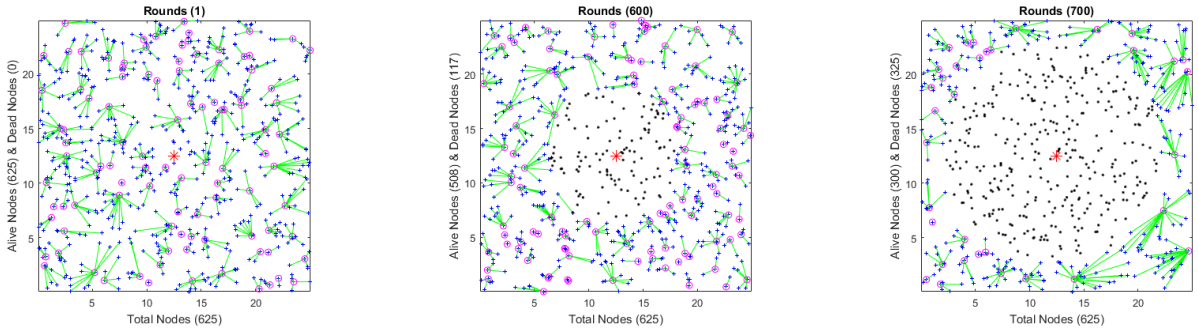

Fig. 5. 625-Node (25m×25m) Dense Random Network with Fixed Density (Initial Round, Round 600, Round 700)
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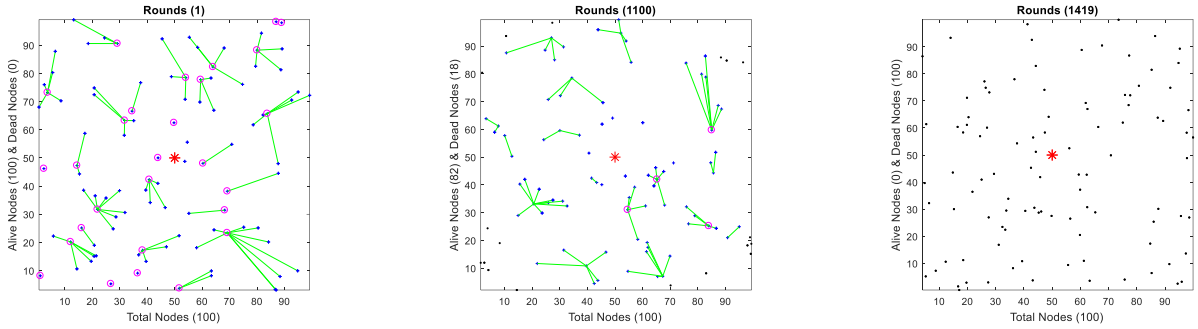

Fig. 6. 100-Node (100m×100m) Sparse Random Network (Initial Round, Round 1100, Final Round)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

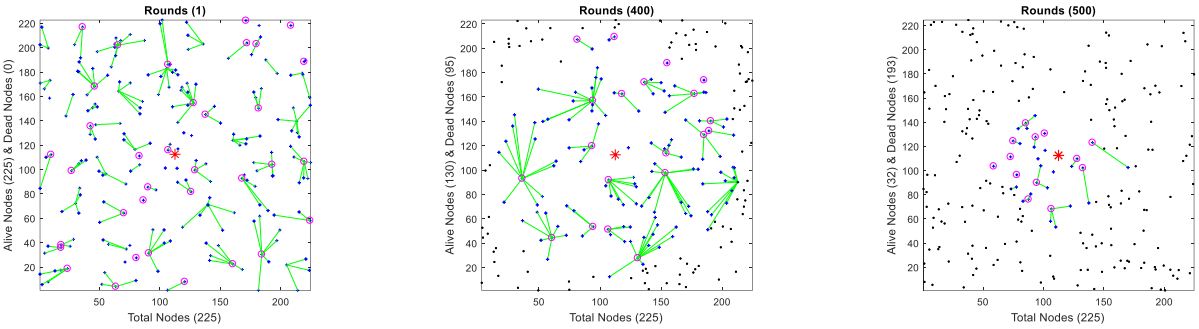

Fig. 7. 225-Node (225m×225m) Sparse Random Network (Initial Round, Round 400, Round 500)
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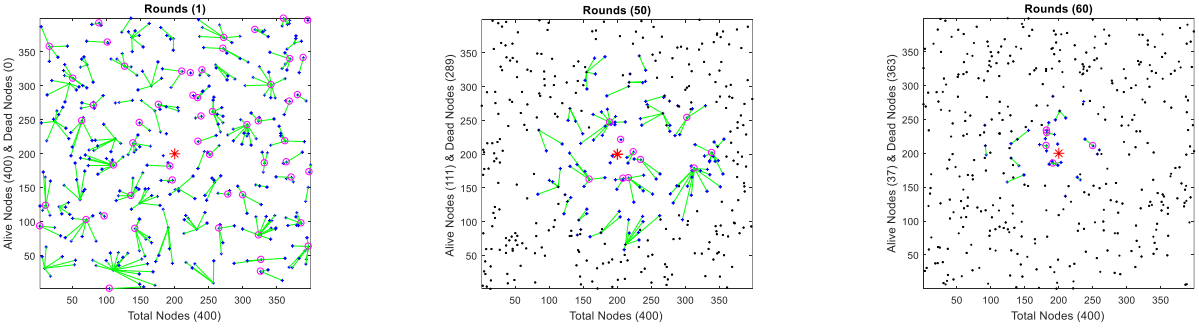

Fig. 8. 400-Node (400m×400m) Sparse Random Network (Initial Round, Round 50, Round 60)
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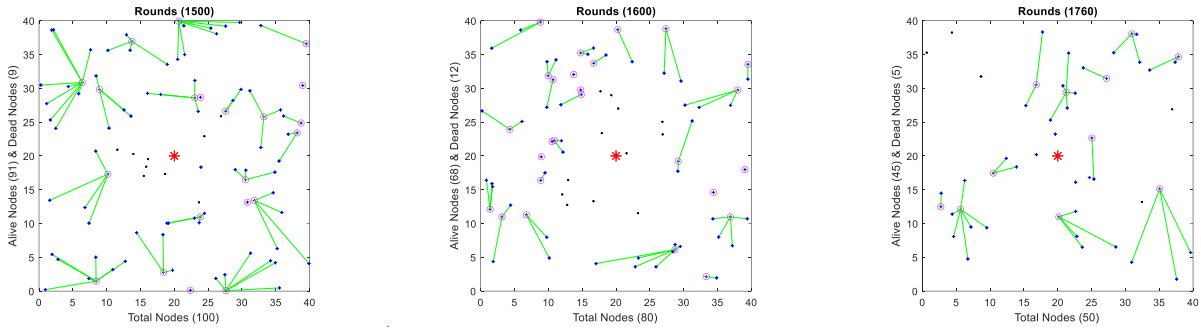

Fig. 11. Random Network Lifetime Analysis Fixed Scalability (40m×40m)
Blue "+": Active Sensor Node; Pink "o: Cluster Head; Red "*": Sink Node; Black ".": Dead Node; Green lines: Single-Hop Routing Paths.

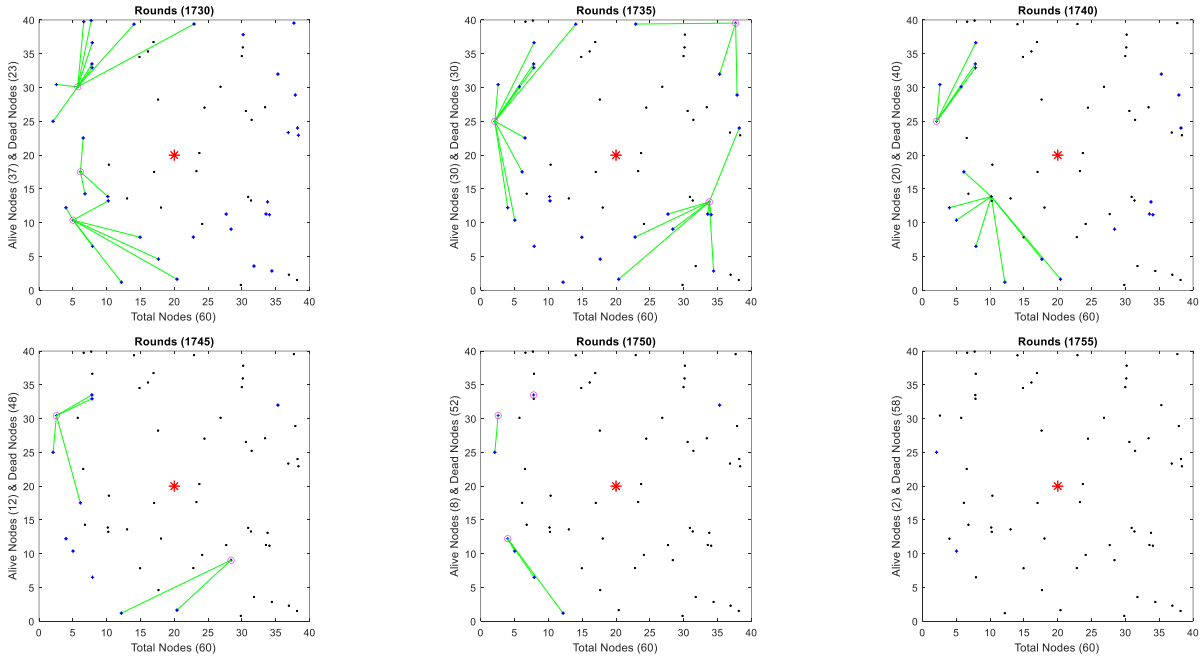

Fig. 12. Lifestime Synthesis of Near-Optimal Sensor Node Deployment at Rounds 1730, 1735, 1740, 1745, 1750, and 1755
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