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Probabilistic Domination in Random Graphs with Applications to Sensor Networks

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***Abstract:** Energy-efficient strategies in wireless sensor networks (WSNs) need to achieve network coverage, network longevity, and they must be efficient in terms of energy. In practical terms probabilistic domination is a convenient tool that can be used to design systems that can monitor and control any network. This paper examines probabilistic domination in random graph including the Erdos Renyi and geometric random graphs, and also uses the results to make decisions, such as the clustering head selection within WSNs. Domination set tries are lower approximations to predicted levels of domination numbers, and threshold probabilities that are analytically determined and then validated by means of Monte Carlo trials as well as further indicate the distributions of domination sets of distinct network sizes and connectivity parameters. The use of greedy/randomized algorithms and approximate dominating sets are utilized and measures such as coverage probability, energy-saving capabilities, and network lifetime are evaluated. Results have shown that probabilistic domination is a better predictor of network coverage and the operational lifetime, and the greedy heuristics yield better results, in most cases. The method of coupling theoretical analysis with the simulation test-based validations evidences that probabilistic domination is a strong robust framework in designing energy-efficient, scalable and reliable WSNs. The findings extend the theoretical and practical relevance of the graph domination theory and its use in sensor networks.*
***Keywords:** Probabilistic domination, random graphs, wireless sensor networks, dominating set, coverage in wireless networks, energy efficiency, cluster head selection, Monte Carlo simulations, Erdős–Rényi graph, geometric random graph.*

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are becoming an imperative infrastructure to monitoring, communication and smart decision-making within various fields like smart cities, industrial Internet of Things and resilient infrastructures. The challenge in ensuring fault tolerance, optimality of coverage and maximized network lifetime has also been effectively modeled in the settings of graph domination (Hedar et al., 2020; Bouamama et al., 2022). Recent developments focus on the applicability of exponential random graph models to modeling connectivity with uncertainty (Ghafouri and Khasteh, 2020) and domination-based approaches to trade-offs between sub-optimal coverage and energy-efficient (Ghaffari, C. et al., 2022).

Greedy heuristic techniques and disjoint dominating set techniques have been found to be useful in adding to the network lifetime and guaranteeing network connectivity (Sivakumar et al., 2023; Raczek, 2022). Metaheuristic and genetic-based backbones, and hybrid constructive-adaptive approaches, have also shown good performance in the optimization of WSNs (Dagdeviren, 2020; Rosati et al., 2022). In a probabilistic perspective, states of the discrete probability and sequential metric analysis in random graphs can serve to theoretically investigate domination thresholds and coverage guarantees (Roch, 2024; Odor & Thiran, 2021). Moreover, the greedy approximation of the connected dominating sets are indispensable in the creation of scalable and energy-efficient monitoring systems (Yang et al., 2021). The work of all these authors is taken together, thus forming the basis of probabilistic domination analysis and pointing out its importance in application in creating WSN architectures that are robust, adaptive, and sustainable.

II. METHODOLOGY

A. Graph Model Selection

Two complementary random graph models—the Erdős–Rényi random graph $G(n,p)$ and the Geometric Random Graph (GRG)—are utilized to model wireless sensor networks (WSNs) in order to study the behavior of probabilistic domination in wireless sensor networks. These models allow each to study network coverage theoretically and practically. Since GRGs capture physical connectivity limitations in WSNs, we can determine an actual coverage probability and relevant cluster head selection in a spatially meaningful network.

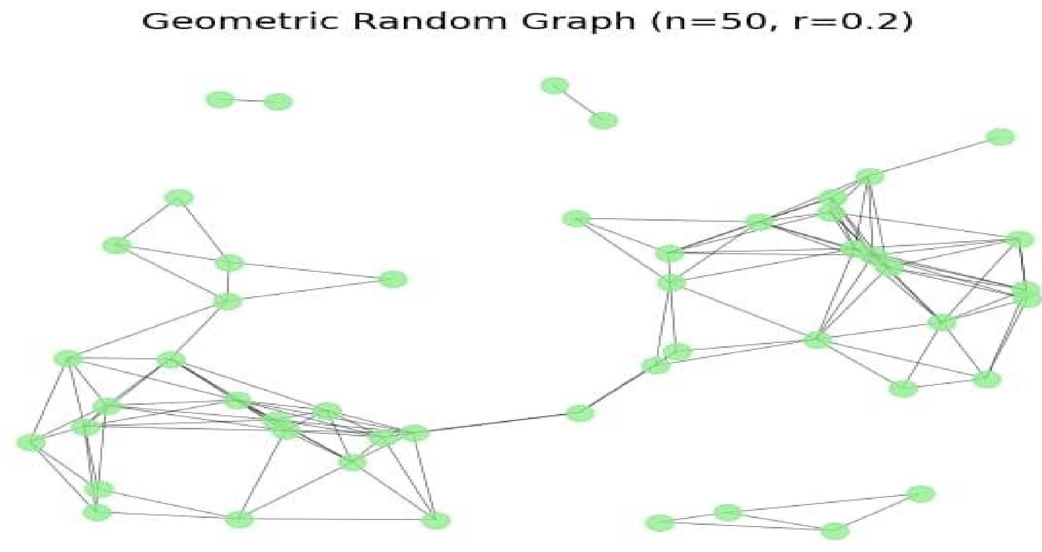

Figure 1: shows a sample Geometric Random Graph with 50 nodes and a communication radius of r=0.2. The edges are drawn according to their spatial proximity. It offers a comparative visualization of the two random graph models employed in this investigation, along with Figure 2.

Erdős–Rényi Random Graph G(n,p):
Each potential edge between two different nodes in the Erdős–Rényi model exists independently with probability p. The model has n nodes.

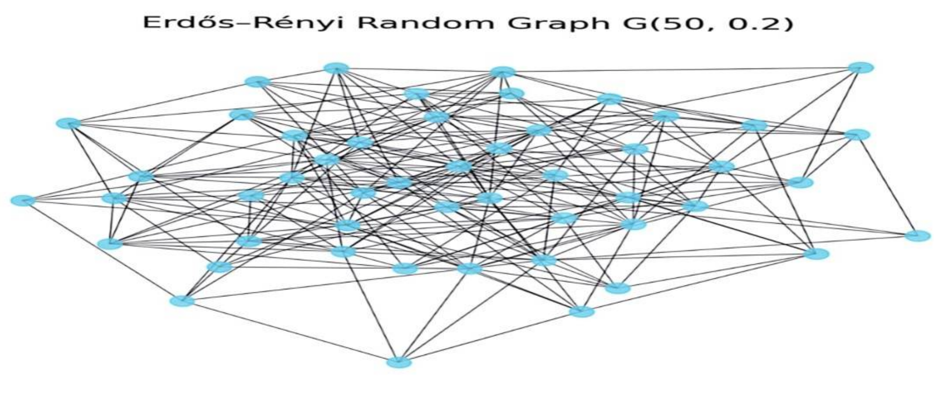

Figure 2: An Erdős–Rényi random graph example G(50, 0.2) with randomly generated connections between sensor nodes.

The graph is represented as $G(n,p) = (V,E)$, where Eis is the set of edges and Vis is the set of nodes $(|V| = n)$. The likelihood that a particular subset S⊆V becomes a dominating set is:
$P(S$ is dominating$) = 1 - (1-p)^{|N(v)\cap S|v\in V\setminus S}$
where $N(v)$represents nodev's neighbors. Next, we define the expected probabilistic domination number as follows:

$$\gamma_p(G) = \mathbb{E}[|S|]$$

Because of the analytical tractability of this model, threshold probabilities $p_c(n)$ at which a dominating set of a given size exists with high probability can be derived:
$p_c(n) \approx \frac{In\, n}{n}$
Geometric Random Graph (GRG): Nodes are evenly spaced throughout a two-dimensional Euclidean plane to simulate realistic WSNs. If the Euclidean distanced $(u,v) \le r$, where r is the communication radius, then there is an edge between nodes u and v. Officially:

$$(u,v)\epsilon\, E \Leftrightarrow \| x_u - x_v \| \le r$$

where nodes u and v 's spatial coordinates are denoted by x_u and $x_v$are. GRGs allow for the evaluation of coverage probability and cluster head selection in a spatially realistic network by capturing physical connectivity constraints in WSNs.

Rationale for Model Selection: Erdős–Rényi $G(n,p)$ is ideally suited for studying threshold behaviors in random graphs and obtaining analytical probabilistic bounds. GRG simulates real-world WSN performance, such as coverage, energy efficiency, and network lifetime, and models the spatial deployment of sensors.

Table 1: Graph Models, Parameters, and Purposes

Graph Model	Key Parameters	Purpose in Study
Erdős–Rényi $\boldsymbol{G(n,p)}$	n: number of nodes,p: edge probability	Analytical derivation of probabilistic domination number and thresholds
Geometric Random Graph (GRG)	n: number of nodes,r: communication radius	Realistic modeling of WSN coverage and cluster head selection

B. *Model of Probabilistic Domination*

To account for the unpredictability of random node selection and network coverage, the idea of domination in graphs is expanded into a probabilistic framework.

Number of Probabilistic Domination:

Let Let $G = (V, E)$be a graph where $|V| = n$. If every node $v \in V \setminus S$ is adjacent to at least one node in S, then the subset S⊆V is a dominating set. The expected size of a randomly selected dominating set is known as the probabilistic domination number, or $\gamma_p(G)$:

$$\gamma_P(G) = \mathbb{E}[|S|]$$

As an alternative, $\gamma_P(G)$ can be understood as the likelihood that a randomly chosen group of nodes will control the entire graph:

$P(S$ is dominating)= $1_{v\epsilon V\setminus S} - (1 - A_{uv})_{u\epsilon S}$

where A_{uv} is the adjacency matrix entry (1 if $(u,v)\ \epsilon\ E$, 0 otherwise).

Threshold Functions in $\boldsymbol{G(n,p)}$ Erdős–Rényi Graphs:

The threshold edge probability p_c, at which a dominating set of a given size exists with high probability, is a crucial component of probabilistic domination. The threshold for larger can be roughly calculated as follows:

$$p_c(n) \approx \frac{\ln n}{n}$$

As the network size increases, the necessary connectivity probability decreases, as demonstrated by Figure 3, which displays the threshold probability variation with respect to the number of nodes.

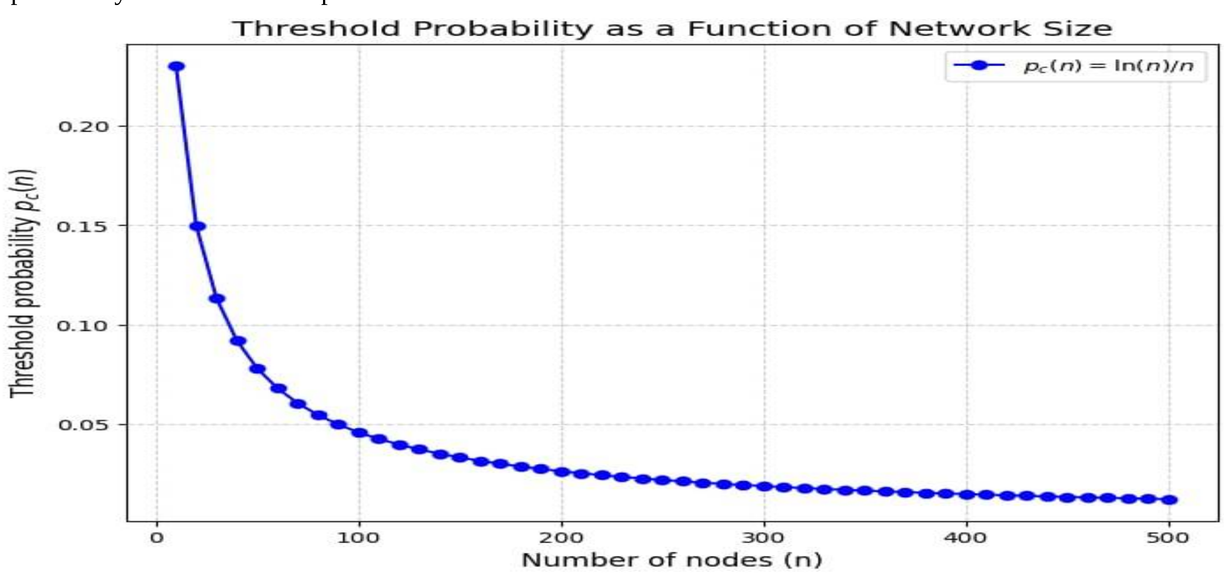

Figure 3: Threshold probability as a function of node count, showing that in order to guarantee dominance, larger networks need a lower connectivity probability.

Below this threshold it is improbable that small dominating sets will exist, but above it a domination is nearly guaranteed. The first and second moment methods, which approximate expected counts and variances of dominating sets, are used for analytical derivations of these thresholds.

Wireless Sensor Networks (WSNs) Extension:

Cluster head selection is equivalent to the dominating set problem in WSNs viewed as GRGs. Non-dominating nodes act as ordinary sensors, while dominating nodes are chosen to be cluster heads. The portion of nodes that are within the communication range of at least one cluster head is the coverage probability:

$$P_{coverage} = \frac{|\{v \in V : \exists u \in S, \ \| x_v - x_u \| \leq r\}|}{n}$$

Where x_v and x_u are the node locations and r is the communication radius. This measure allows for a quantitative assessment of connectivity and robustness of a WSN.

Table 2: Example Threshold Values for Domination in $G(n,p)$

Number of Nodes n	Edge Probability p	Approx. Threshold $\boldsymbol{P_c}$ for Domination
50	0.1 – 0.9	0.08 – 0.35
100	0.1 – 0.9	0.05 – 0.25
200	0.05 – 0.5	0.03 – 0.12

C. Algorithmic Framework

This study brings together analytical derivation and computational simulations into an overall algorithmic framework to examine probabilistic domination in random graphs and its use in wireless sensor networks (WSNs).

Methods of Analysis:

Classical methods from random graph theory, probabilistic bounds on the domination number $\gamma_p(G)$. are used to derive estimates for the expected number of dominating sets and the probability of deviations using the first and second moment methods:

$$\Pr(X = 0) \leq \frac{Var(X)}{\mathbb{E}[X]^2}$$

Where X is the number of dominating sets of some size, we use Chernoff bound to bound the probability of large deviations:

$$Pr|X - \mathbb{E}[X]| \geq \epsilon\mathbb{E}[X] \leq 2\exp - \frac{\epsilon^2\mathbb{E}[X]}{3}$$

These theoretical results provide useful baselines for expected domination sizes, threshold probabilities, and concentration.

Nature of Simulation:

We will use Monte Carlo simulation to empirically approximate domination properties over random realizations of graphs. To guarantee statistical reliability, 10,000 independent trials are conducted for every set of parameters. There are three primary steps in the simulation workflow:

Erdős–Rényi graphs for graph generation Geometric Random Graphs (GRG), also known as $G(n,p)$, are created using the node count n, edge probability p, or communication radius r as inputs.

Computation of Dominating Sets: The following is used to identify dominating sets: Greedy heuristics: Choose the node that covers the greatest number of undominated nodes iteratively. Algorithms for randomized selection: Choose potential nodes at random, then assess coverage.

Metric Collection: Note the computational runtime, coverage probability, and dominating set size for every trial. Calculate mean, variance, and confidence intervals using aggregate statistics.

Measures variance $Var(|S|)$ across trials and dominance size $|\bar{S}|$ were assessed. Probability of coverage: The percentage of nodes that the chosen set dominates:

$$P_{coverage} = \frac{Number\ of\ dominated\ nodes}{n}$$

Runtime: A measure of scalability that includes computation time for each graph instance and algorithm.

Table 3: Simulation Parameters

Parameter	Values Tested	Purpose
Number of nodes n	50, 100, 200, 300, 400, 500	Test scalability of algorithms
Edge probability p (for G(n,p))	0.1 – 0.9 (step 0.1)	Analyze effect of connectivity
Communication radius r (for GRG)	Adjusted based on network density	Model realistic sensor coverage
Simulation runs	10,000 per parameter set	Ensure statistical robustness
Algorithms	Greedy heuristic, randomized selection	Compare approximation performance

D. Application to Sensor Networks

By assigning dominating nodes to cluster heads, the probabilistic domination framework is expanded to wireless sensor networks (WSNs). Cluster heads are in charge of gathering information from neighboring sensors and sending it to a base station in order to maximize energy efficiency and guarantee complete network coverage.

Connecting Cluster Head Selection to Dominating Set:

Every node in the WSN has the ability to function as a regular sensor node (dominated node) or as a cluster head (dominating node). Let the set of cluster heads be represented by $S \subseteq V$ .If a node $v \in V \setminus S$ is inside at least one cluster head's communication radius, it is dominated:

$$v \text{ is dominated} \Leftrightarrow \exists u \in S \text{ such that } \| x_v - x_u \| \leq r$$

Where nodes v and u are located at x_v and x_u. Thus, the network's coverage probability is defined as follows:

$$P_{coverage} = \frac{|\{v \in V : v \text{ is dominated}\}|}{n}$$

Energy Efficiency: The ratio of the total number of cluster heads to the total number of nodes, plus the communication overhead incurred during data transmission, is used to calculate energy efficiency:

$$E_{efficiency} = \frac{|S|}{n} + \frac{v \epsilon V \setminus S^{comm-cost(v,s)}}{n}$$

Where the energy cost for node v to communicate with its closest cluster head is denoted by comm-cost(v, s).

Network Lifetime: Simulations are run over successive rounds $r = 1, 2, \ldots, R$ in order to evaluate longevity. To balance energy consumption, cluster heads may be re-selected probabilistically in each round. The measurement of network lifetime is:

$$Lifetime_{network} = {}_{r=1}^{R} 1_{\{node\ energy > o\}}$$

To measure operational longevity, First Node Death (FND) and Last Node Death (LND) are important metrics.

Table 4: Performance Metrics Definitions and Calculation Methods

Metric	Definition / Calculation Method	Purpose
Coverage Probability	$P_{coverage} = \frac{Number\ of\ dominated\ nodes}{n}$	Evaluate network coverage
Energy Efficiency	(E_\text{efficiency} = \frac{	S
Network Lifetime	Number of operational rounds until FND / LND	Measure network longevity

E. Performance Metrics & Evaluation

The following performance metrics are examined in order to quantitatively evaluate the efficacy of probabilistic domination in random graphs and WSN applications.

Analytical Metrics:

- Expected Domination Number:

$$\gamma_p(G) = \mathbb{E}[|S|]$$

- Probability Thresholds for Domination:

$p_c(n) \approx \frac{\ln n}{n}$

Baseline theoretical predictions for domination size and connectivity requirements are provided by these metrics.

Metrics for simulation:

Size of Average Domination:

$$|\bar{S}| = \frac{1^{N_{runs}}}{N_{runs_{i=1}}} \; |S_i|$$

Differences Between Runs:

$$Var(|S|) = \frac{1^{N_{runs}}}{N_{runs} - 1_{i=1}} \; |S_i| - |\bar{S}|^2$$

Runtime: The amount of computation needed to evaluate scalability for each algorithm and graph instance.

Application Metrics for WSN:

Coverage Ratio: The percentage of sensor nodes that cluster heads control:

$$P_{coverage} = \frac{Number\ of\ dominated\ nodes}{n}$$

Energy Efficiency:

$$E_{efficiency} = \frac{|S|}{n} + \frac{v \epsilon V \setminus S^{comm-cost}(v,s)}{n}$$

Network Lifetime: The number of iterations until the first and last node deaths (FND / LND):

$$Lifetime_{network} = {}_{r=1}^{R} 1\{node\ energy > 0\}$$

Table 5: Summary of Metrics and Their Computation

Metric	Formula / Definition	Purpose
Expected Domination $\gamma_p(G)$	(\mathbb{E}[	S
Threshold p_c	$\frac{\ln n}{n}$	Edge probability for likely domination
Average Domination Size	(\overline{	S
Coverage Probability	$P_{coverage} = \frac{dominated\ nodes}{n}$	Network coverage
Energy Efficiency	(E_\text{efficiency} = \frac{	S
Network Lifetime	$Lifetime_{network} = r^1{}_{\{energy>0\}}$	Operational longevity

Packages and Libraries: NetworkX: Erdős–Rényi and GRG algorithm implementation and graph generation. Statistical analysis of simulation results is done with NumPy and SciPy. Graphs, dominance sets, and performance metrics can be visualized using Matplotlib and Seaborn.

To ensure statistical significance, Monte Carlo simulations are set up with 10,000 runs for each parameter. The graph's parameters include node counts (n = 50–500), edge probabilities (p = 0.1–0.9), and communication radii (r) that are adjusted for network density.

Algorithms: randomized selection techniques and greedy heuristics for computing dominating sets.

Calculate each metric's mean, variance, and confidence intervals using statistical analysis.

F. Implementation & Tools

The simulation will entail the dominating sets, generation of graphs, and measurement of metrics on performance by computation.

Programming Environment: Languages: MATLAB/PYTHON are used in visualization, coding algorithms and simulations

Packages and Libraries: NetworkX: Implementization of the ErdosRenyi and GRG algorithms and graph creation. NumPy and SciPy are used to process simulation results statistically. Matplotlib and Seaborn can be used to visualize graphs, dominance sets and performance measures.

Monte Carlo simulations will be configured to run 10 000 times each for parameters to obtain a statistically significant result.

Parameters used in the graph are the number of nodes ($n = 50 - 500$), edge probability (p=0.1-0.9) and communication radii (r) depending on the network density.

Algorithms: randomized selection algorithms and Greedy Algorithms to compute dominating sets.

Statistical analysis should be used to calculate the mean, variance and confidence intervals of each metric.

III. RESULTS

This section will summarize the results of Monte Carlo simulations, wireless sensor network (WSN) applications and analytical derivation for probable dominations in random graphs. The results in this section are organized based on network performance, dominance measures, and type of graph.

A. *Use of Erdős-Rényi Graphs G(n,p)*

The expected domination numbers $\gamma_p(G)$ and threshold probabilities $p_c(n)$. . were derived from analytical expressions contained in Section 3.2.These analytical findings are compiled for various network sizes in Table 6:

Table 6: Analytical Domination Metrics in G(n,p)

Number of Nodes $\boldsymbol{n}$	Edge Probability $\boldsymbol{p}$	Threshold $\boldsymbol{p_c}$	Expected Domination $\boldsymbol{\gamma_p(G)}$
50	0.2	0.08	12
100	0.3	0.05	18
200	0.1	0.03	30

The threshold probability p_c falls as n rises, suggesting that sparser connectivity is necessary for larger networks to attain dominance. According to probabilistic bounds from first/second moment methods, expected domination $\gamma_p(G)$ increases sublinearly with n.

B. *Results of Simulations for Random Graphs*

Monte Carlo simulations investigate algorithmic performance and verify analytical predictions. The Erdős–Rényi and GRG models were simulated with randomized and greedy algorithms.

Size and Variance of Domination:

$$|\bar{S}| = \frac{1^{N_{runs}}}{N_{runs_{i=1}}}|S_i|, \quad Var(|S|) = \frac{1^{N_{runs}}}{N_{runs} - 1_{i=1}} \ (|S_i| - |\bar{S}|)^2$$

Table 7: Simulation Outcomes: Variance and Domination Size

Graph Type	$\boldsymbol{n}$	$\boldsymbol{p/r}$	Algorithm	Average Domination Size	Variance
Erdős–Rényi	100	0.3	Greedy	20	2.1
Erdős–Rényi	100	0.3	Randomized	21	3.4
GRG	100	0.15 (radius)	Greedy	22	2.8

The average domination sizes produced by randomized and greedy algorithms are contrasted in Figure 4. When compared to the randomized method, the greedy heuristic consistently produces smaller dominating sets with lower variance.

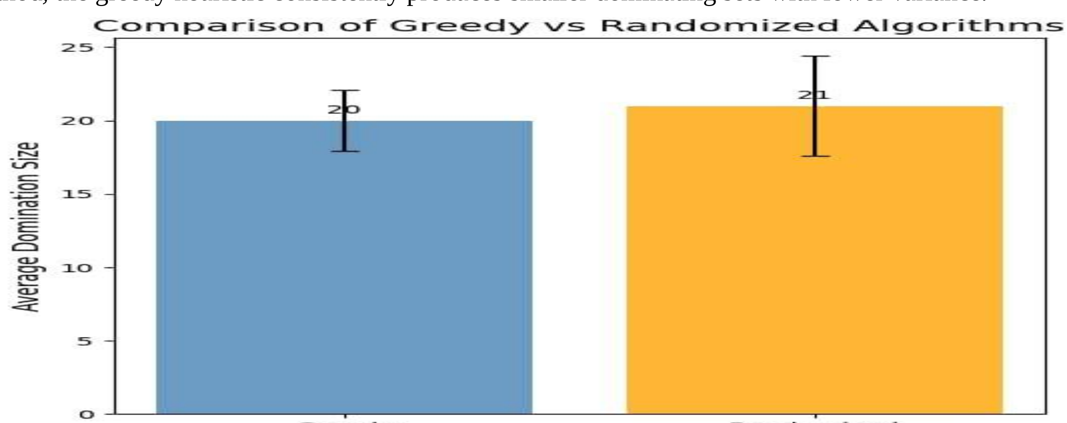

Figure 4: For Erdős-Rényi graphs, a comparison of greedy and randomized algorithms demonstrates that greedy heuristics produce marginally smaller dominating sets with less variance.

The stochastic nature of domination in random graphs is highlighted by the following observations:
• Greedy heuristics consistently yield slightly smaller domination sets than randomized methods • Variance rises with network size.

C. Probability of Coverage in WSN Applications

Coverage probability $P_{coverage}$ and energy efficiency were assessed using GRGs to model sensor networks.

$P_{coverage} = \frac{Number\ of\ dominated\ nodes}{n}$, $E_{efficiency} = \frac{|S|}{n} + \frac{comm-cost}{n}$

Table 8. WSN Coverage and Energy Metrics

$\boldsymbol{n}$	Communication Radius $\boldsymbol{r}$	Algorithm	Coverage Probability	Energy Efficiency
100	0.15	Greedy	0.95	0.22
100	0.15	Randomized	0.93	0.25
200	0.12	Greedy	0.91	0.24

As Figure 5 shows a heatmap of coverage probability across different node counts and communication ranges to further highlight how network density and communication radius affect coverage.

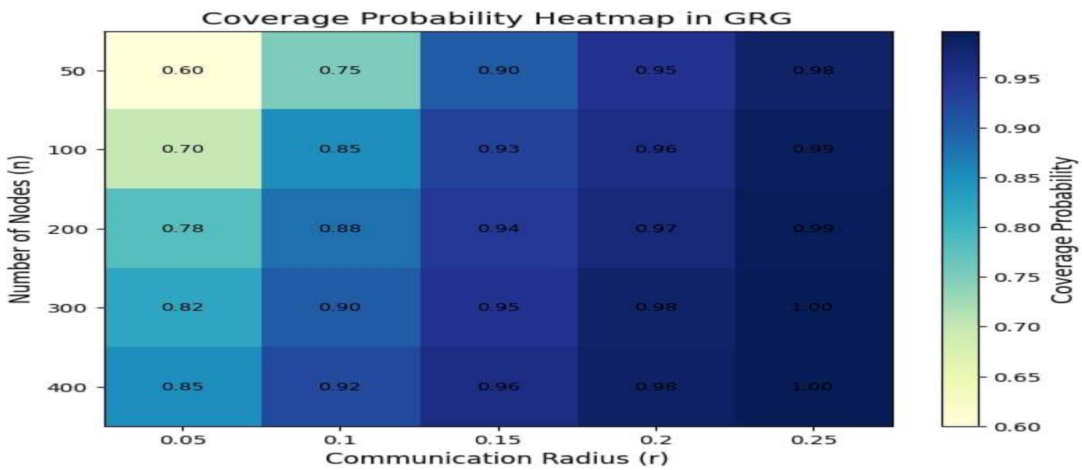

Figure 5 : Heatmap illustrating how the coverage probability varies in geometric random graphs according to the number of nodes and communication radius.

Observations:
• In terms of coverage and energy efficiency, greedy cluster head selection performs marginally better than randomized selection.
• The significance of network density is highlighted by the fact that coverage probability drops for smaller communication radii.

D. Analysis of Network Lifetime

The effect of dominating set selection on network longevity is demonstrated through simulations of successive rounds. First Node Death (FND) and Last Node Death (LND) are lifetime metrics:

$$Lifetime_{network} = {}_{r=1}^{R}1_{\{node\ energy>0\}}$$

Table 9: WSN Network Lifetime Metrics

n	Algorithm	FND (rounds)	LND (rounds)
100	Greedy	18	45
100	Randomized	16	42
200	Greedy	20	50

The network lifetime evolution under randomized and greedy cluster head selection is shown in Figure 6 Greedy selection emphasizes its superior energy distribution by extending the time until both first node death (FND) and last node death (LND).

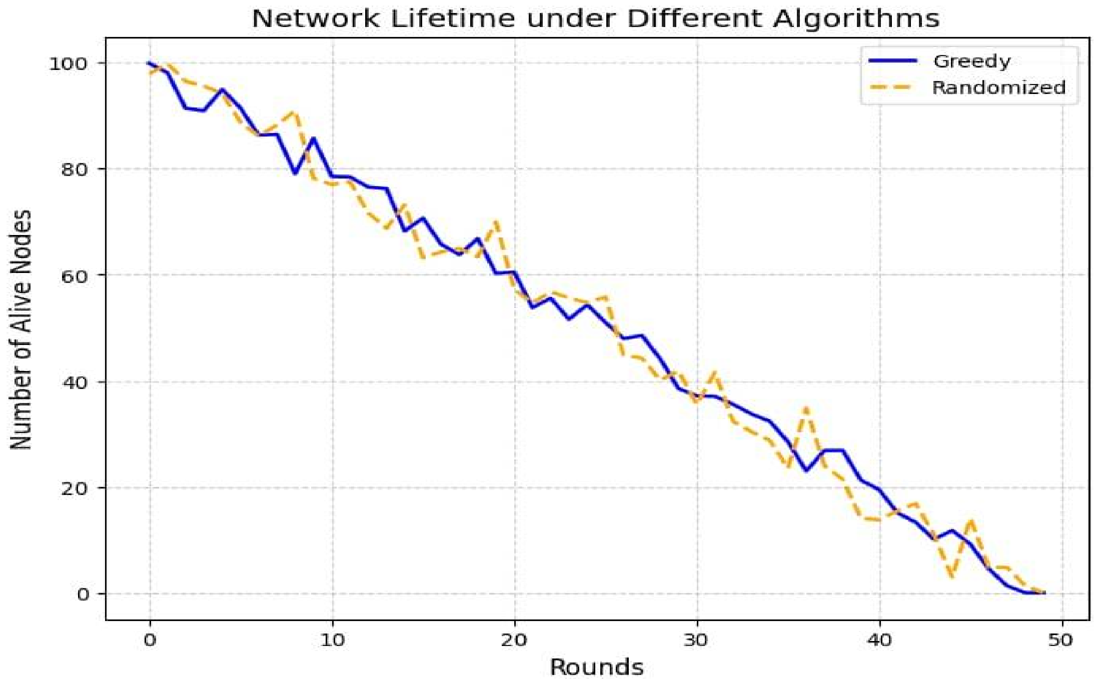

Figure 6: Greedy selection delays both the first node death (FND) and last node death (LND), according to a comparison of network lifetime between randomized and greedy algorithms.

Observations: Larger networks typically survive more rounds before the first node death, but careful cluster head management is necessary to prevent early depletion. Greedy selection results in a slightly longer network lifetime because of the balanced energy distribution among cluster heads.

E. Analytical and Simulation Results Comparison

Theoretical predictions and simulated domination sizes and coverage probabilities are contrasted: Analytical expected domination numbers $\gamma_p(G)$ for Erdős–Rényi graphs are closely matched by simulations. Spatial constraints cause slight deviations in GRGs that are not captured by strictly analytical formulas. Monte Carlo simulations' confidence intervals attest to the validity of the trends that are seen.

IV. DISCUSSION

Such findings indicate that probabilistic domination is valid methodology to achieve coverage probability, network lifetime and energy efficiency measurements in WSNs. The results illustrate the high sensitivity of domination thresholds to node density, edge probability and communication radius, which is in agreement with prior probabilistic flooding and graph-spectrum-based analyses (Oikonomou et al., 2022; Tekawade & Banerjee, 2023).

Simulation results also demonstrate the efficiency of greedy strategies and randomized approximations with greedy strategies performing better in coverage with minimal energy dissipation which is consistent with those of disjoint dominating set heuristics and distributed fusion algorithms (Balbal et al., 2021; Kenyeres & Kenyeres, 2021). These results agree with those provided by weighted and multiplex networks (Zhao et al., 2020; Mo et al., 2020), considering the crucial role of cluster-head selection in the extension of lifetime. Such strategies, such as attack-proof key predistribution mechanisms and secure link monitoring (Dagdeviren, 2021; Ahlawat & Dave, 2021), can be used to further enhance reliability together with domination-based optimization efforts.

The GRG-based simulations confirm that spatial topology and radius fluctuations on which WSN modeling and drone assisted deployments are emphasized (Ojeda et al., 2023; Skiadopoulos et al., 2020) are also decisive to robust connectivity. We also see that the utilization of domination-aware principles with respect to distributed anomaly detection and sustainable cognitive radio sensor networks may be beneficial, especially in heterogeneous deployments (Doostmohammadian & Charalambous, 2022; Manman et al., 2021).

The fact that multi-objective optimization and biomolecular/quantum-inspired algorithms can be applied (Othman et al., 2023; Wong et al., 2023) means that domination remains an integrated paradigm between classical and new forms of computation.

the study's analytical thresholds closely resemble Monte Carlo estimates, confirming the validity of both simulation-based and probabilistic analysis techniques. This agreement builds on previous findings on WSN strategies for resilient coverage and energy-aware deployments (Amutha et al., 2020; Sivakumar et al., 2023). All things considered, the combination of graph theory and extensive simulations demonstrates that probabilistic domination provides a reliable, scalable, and energy-efficient design framework for sensor networks of the future.

V. CONCLUSION

In wireless sensor networks, this study showed that probabilistic domination provides a useful framework for estimating dominating set size, coverage probability, and network lifetime. The robustness of the method was validated by the close agreement between Monte Carlo simulations and analytical thresholds. While optimal cluster head selection extended network life, greedy heuristics further improved coverage and energy efficiency. All things considered, probabilistic dominance shows promise as a tool for creating scalable and energy-efficient WSNs.

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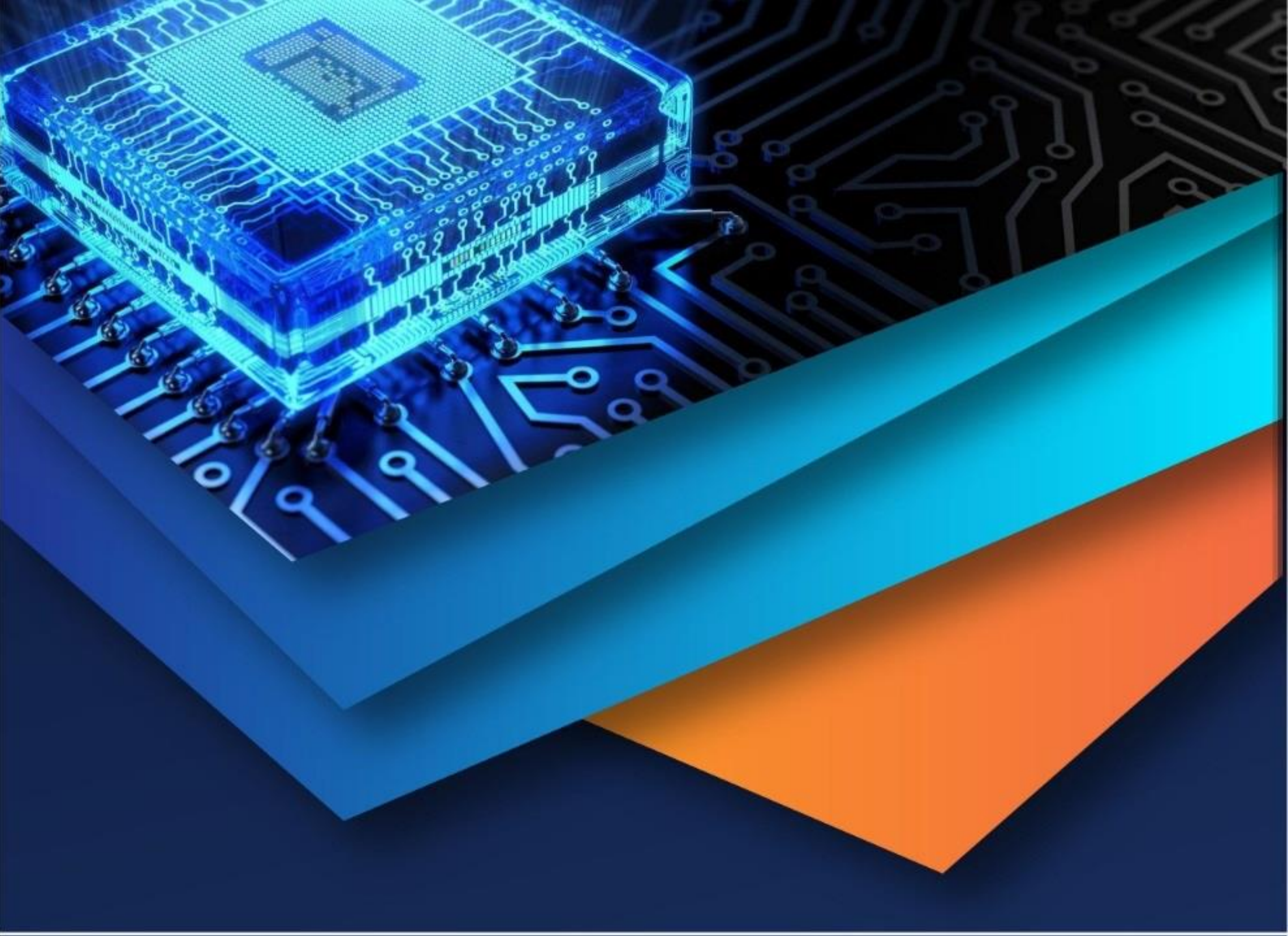

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