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Comparative Analysis of Mesh and Torus Topologies versus Gaussian Connection Models in Wireless Sensor Network

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Abstract*— Wireless Sensor Networks (WSNs) are critical for modern applications such as environmental monitoring, industrial automation, and smart cities. Traditional network topologies like mesh and torus offer reliability and redundancy but face limitations including high energy consumption, edge congestion, and rigid structure, especially in large-scale deployments. Gaussian connection models address these challenges by adopting a probabilistic and adaptive clustering approach. Nodes connect based on a Gaussian distribution considering distance, energy level, and other metrics, enabling balanced load distribution, energy efficiency, and robust fault tolerance. Advanced algorithms such as LEGN and TEGN leverage Gaussian models to optimize cluster head selection and routing, significantly improving network lifetime and reducing packet loss and latency. Comparative analysis shows Gaussian models outperform mesh and torus topologies in scalability, energy efficiency, and adaptability. This paper highlights their advantages through algorithmic insights, implementation case studies, and performance comparisons, justifying Gaussian connection models as an optimal choice for next-generation WSNs. Future work will explore hybrid models and deeper reinforcement learning to further enhance performance.

Keywords: Adaptive Clustering, Energy Efficiency, Gaussian Connection Model, Network Topology, Wireless Sensor Networks (WSNs).

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are networks composed of spatially distributed sensor nodes that collaboratively monitor physical or environmental conditions such as temperature, sound, or motion. The term “wireless” refers to the use of radio frequency communication without physical cabling, “sensor” denotes the devices capable of detecting and transmitting data, and “network” signifies the interconnected structure that allows data exchange among nodes [1]. These distributed nodes are autonomous devices spread across a geographical area, collectively performing sensing and communication tasks. Since each node operates independently yet cooperatively, their distributed nature ensures scalability and resilience, even when individual nodes fail. A major challenge in WSNs lies in their energy constraints, as most sensor nodes rely on limited battery power and are often deployed in remote or inaccessible regions. Energy efficiency, therefore, becomes crucial to prolong the network’s operational lifetime [2]. The necessity for adaptive topology management arises from the dynamic nature of WSNs—nodes may join, fail, or move over time. Topology management refers to maintaining and optimizing the structure of node connections to ensure efficient communication, balanced energy consumption, and sustained coverage. Adaptive mechanisms allow the network to reorganize itself automatically to maintain performance despite environmental or operational changes. Traditional topologies like mesh and torus were initially adopted due to their structural reliability. A mesh topology connects nodes in a web-like pattern, providing multiple communication paths between any two nodes. A torus topology extends the mesh by connecting boundary nodes to form a loop, reducing edge effects. These topologies provided redundancy, meaning that if one link failed, alternate routes could still transmit data—enhancing fault tolerance [3]. They were considered robust because the network could continue functioning smoothly even when some nodes were inactive or damaged. However, as WSNs expanded in scale and data transmission increased, these rigid deterministic models revealed several limitations. They struggled with high energy consumption due to constant multi-hop communication, uneven load distribution among nodes, and boundary effects where peripheral nodes experienced reduced connectivity and faster energy depletion. These challenges can be mitigated by employing probabilistic connectivity models, energy-aware routing protocols, and adaptive clustering mechanisms that dynamically balance load and conserve energy [4].

In recent years, Gaussian connection models have gained attention for addressing these issues. These models define node connectivity based on a probability distribution rather than fixed distances, allowing for more flexible and realistic network structures. By promoting probabilistic clustering and adaptive communication ranges, Gaussian models enhance scalability and reduce energy waste. Advanced energy-efficient algorithms such as LEGN (Localized Energy-efficient Gaussian Network) and TEGN (Topology-Evolving Gaussian Network) build upon these models. They are considered extremely effective because they intelligently adjust node connectivity and communication radius according to network density and energy availability. This results in optimized routing, balanced energy consumption, and prolonged network lifetime, making them essential for next-generation WSN applications [5].

II. LITERATURE SURVEY

2.1. Mesh Topology in WSN

In a Mesh Topology, every sensor node in the Wireless Sensor Network (WSN) can communicate with multiple neighboring nodes, creating several redundant paths for data transmission. This redundancy improves reliability because even if one path fails, data can be rerouted through another. However, this design also leads to higher energy consumption since nodes often take part in repeated transmissions and multi-hop communication. As a result, the battery power of sensor nodes drains faster, especially in large-scale or dense networks where multiple nodes are active simultaneously [6]. Node scheduling plays a vital role in reducing this energy burden. Swarm-inspired algorithms such as the Artificial Bee Colony (ABC) optimization have been used to manage node placement and activity scheduling. These algorithms imitate the behavior of bees to find the most energy-efficient deployment and communication pattern. While they outperform traditional fixed-placement methods, they still face network congestion when node density increases. This happens because too many nodes try to transmit data at the same time, causing packet collisions and transmission delays [7]. In terms of routing, protocols like R-LEACH (Refined Low-Energy Adaptive Clustering Hierarchy) help manage mesh networks by using centralized cluster heads that collect and forward data to the base station. This reduces the number of direct transmissions and helps balance energy use. However, the main drawback is single-point failure—if a cluster head fails, the communication within that cluster is disrupted. Additionally, boundary congestion occurs when nodes near the edges of the network handle excessive data traffic, leading to uneven energy depletion [8].

The resilience of mesh networks is one of their strongest features. They possess self-healing capability, meaning that when a node fails, the network can automatically reconfigure routes to maintain communication. Yet, to ensure long-term performance, these networks need efficient reprogramming and updating mechanisms that allow nodes to adapt their behavior and firmware without manual intervention. Without such systems, maintenance becomes difficult in large or remote deployments. Mesh topologies are widely used in Industry 4.0 applications, including industrial automation, environmental monitoring, and manufacturing supervision. Their ability to provide stable, redundant, and real-time communication makes them ideal for monitoring machinery, detecting faults, and ensuring safety in smart factories. They are also valuable in remote sensing and environmental systems, where reliable and continuous data collection is essential for decision-making and control [9].

2.2. Torus Topology inn WSNs

A Torus Topology is an advanced variation of the mesh structure, where the nodes located at the boundaries are virtually connected to those on the opposite sides. This loop-like connectivity eliminates network edges, forming a continuous grid pattern. One of the main advantages of this design is balanced load distribution. By linking boundary nodes to each other, the torus topology prevents edge node overloading, which commonly occurs in mesh networks [10]. In a regular mesh, nodes at the edges handle fewer connections and often suffer from uneven data traffic or faster energy depletion. In contrast, the torus structure allows data to circulate more freely in all directions, resulting in a uniform distribution of communication load and better energy efficiency across the network. The multi-dimensionality of the torus network, especially in 3D implementations, enhances its performance further. In a 3D torus topology, nodes are arranged not only horizontally and vertically but also at different altitudes (z-axis). This spatial arrangement helps in optimizing electromagnetic coverage—signals can travel more effectively across different planes—and in reducing interference caused by overlapping transmission paths [11]. As a result, communication becomes more stable and reliable, particularly in dense industrial or urban environments. Another important feature is dynamic clustering. Because of the symmetrical nature of node connections, self- configuration and cluster reassignment can occur more smoothly when nodes join, fail, or move. This symmetry ensures that neighboring nodes can quickly take over the role of a failed one, maintaining connectivity without major disruption. However, this benefit comes with a trade-off— managing a torus topology requires more complex control algorithms and synchronization mechanisms to handle routing, link updates, and energy balancing effectively [12]. In terms of edge handling, the torus topology offers stronger signal coverage and improved reachability, since every node is equally connected within the structure. This reduces packet loss and latency but increases hardware overhead, as maintaining symmetric links demands additional antennas, circuitry, or communication modules. Thus, while performance improves, the network becomes slightly more expensive and resource-intensive to maintain. Torus topologies are widely used in IoT and industrial sensor deployments, where low packet loss, fast reconfiguration, and high reliability are critical. For example, they are found in smart factories, environmental monitoring systems, and industrial automation setups, where continuous data

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transmission and quick adaptation to network changes are essential for real-time operations [13].

2.3. Gaussian Connection Models in WSNs

Gaussian Connection Models represent a modern, probabilistic approach to managing node communication and clustering in Wireless Sensor Networks (WSNs). Instead of using fixed, distance-based links like in traditional mesh or torus topologies, these models rely on probability functions derived from the Gaussian (normal) distribution to determine which nodes connect and how data flows across the network [14]. The probabilistic clustering mechanism allows nodes to join clusters or establish communication links based on the probability that decreases smoothly with distance—following a Gaussian curve. This means that nodes closer to each other have a higher chance of connecting, while distant nodes connect less frequently. This approach ensures balanced connectivity and optimized energy efficiency because communication mainly occurs over shorter, low-power distances while still maintaining overall network coverage. In terms of energy conservation, algorithms that use Gaussian Mixture Models (GMMs) for cluster head selection have demonstrated significant improvements [15]. By modeling node distribution and residual energy as a mixture of Gaussian components, these algorithms form clusters with minimal intra-cluster communication cost—reducing the total energy spent on data transmission and improving the overall network lifetime. This happens because nodes with higher remaining energy and optimal positions are statistically more likely to become cluster heads, thus balancing energy usage among nodes. Another key aspect is noise adaptation. In real-world sensor networks, environmental noise, signal interference, and packet loss can degrade data quality [16]. To overcome this, Gaussian Process Regression (GPR) models and Kalman filters are employed. These tools filter out non-Gaussian noise and predict missing data during communication disruptions, such as those caused by denial-of-service (DoS) attacks. As a result, the network maintains accurate and reliable performance even under harsh or unstable conditions. The adaptive connectivity feature of Gaussian-based clustering is another major advantage. Since cluster head selection and communication patterns are based on continuous statistical updates, the network can automatically adjust to changes in node energy, mobility, or failure. This makes it far more flexible and self-organizing compared to static topologies like mesh or torus, where structure and communication paths are predetermined [17]. Lastly, spatial field reconstruction is a growing application of Gaussian models in WSNs. Using Gaussian Processes, the network can estimate environmental parameters such as temperature, humidity, or pollution levels across large regions with high accuracy and fewer sensors. The statistical inference capabilities of these models allow them to predict values at unsensed locations, making them highly efficient and scalable for smart city and environmental monitoring applications [18].

III. SURVEY AND ANALYSIS

Table 1 presents a comparative analysis of three network models—Mesh, Torus, and Gaussian—based on key performance features. The Gaussian model demonstrates superior scalability, energy efficiency, and fault tolerance due to its adaptive and probabilistic characteristics, making it more robust than the conventional Mesh and Torus models.

Table 1. Comparative Features of Mesh, Torus, and Gaussian Models

Feature	Mesh	Torus	Gaussian
Scalability	Moderate	Good	Excellent
Boundary Issues	Edge effects	Minimized	None (probabilistic)
Energy Efficiency	Fair	Better than Mesh	Best
Cluster Formation	Manual/ Deterministic	Manual/ Deterministic	Statistical/ Adaptive
Fault Tolerance	High	High	Very High

Table 2 compares different network topologies based on their average lifetime and energy consumption using specific routing algorithms. The Gaussian model, employing GMM-DT and DEECGauss algorithms, achieves the longest network lifetime with minimal energy consumption, outperforming traditional Mesh and Torus structures.

Table 2. Network Lifetime and Energy Consumption Comparison

Topology / Model	Algorithm	Avg. Lifetime	Energy Consumed
Mesh	LEACH / R-LEACH	Moderate	Medium
Torus	EEDSR / OEDSR	Good	Lower
Gaussian	GMM-DT / DEECGauss	Excellent	Lowest

Table 3 compares cluster head selection methods in terms of strategy, load balancing, and impact on network longevity. Gaussian probabilistic selection, based on statistical and machine learning models, offers the highest load balancing and network lifetime, making it more efficient than deterministic and torus-adaptive approaches.

Table 3. Cluster Head Selection Efficiency

Method	Selection Strategy	Load Balancing	Network Longevity
Deterministic	Fixed/Manual	Poor	Modest
Torus-Adaptive	Location-based	Good	Longer
Gaussian Probabilistic	Statistical / ML	Excellent	Longest

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IV. JUSTIFICATION FOR GAUSSIAN MODEL SELECTION

The Gaussian Clustering Mechanism in Wireless Sensor Networks (WSNs) provides a probabilistic framework for efficient cluster formation and energy management. In this mechanism, each node calculates the probability of joining a cluster using a Gaussian distribution that considers the distance to cluster heads, residual energy, and other sensor-specific performance factors such as transmission rate or sensing precision [19]. This probabilistic computation ensures that nodes closer to cluster heads and with higher energy levels have a greater chance of participation, thereby reducing transmission power consumption and extending network life. During the clustering phase, the system iteratively refines the mean (μ) and variance (σ^2) of the Gaussian distribution to achieve an optimal and balanced cluster configuration. The mean represents the central node position or the expected cluster center, while the variance defines the spatial spread of nodes within the cluster. These parameters are dynamically tuned after each iteration to maintain uniform node distribution and minimize intra-cluster communication costs. This adaptive mechanism helps prevent congestion, ensures stable communication, and enhances the energy balance across the network [20].

The cluster head selection process integrates both log-likelihood estimation and Dijkstra's shortest path algorithm. The log-likelihood computation identifies the nodes most statistically suited to act as cluster heads based on their Gaussian fitness values, such as high energy and central proximity. Once the cluster heads are chosen, Dijkstra's algorithm calculates the most energy-efficient and shortest communication routes between the heads and the sink node [21]. This hybrid selection process minimizes redundant transmissions, decreases latency, and guarantees reliable data delivery throughout the network. In terms of implementation performance, several empirical case studies have demonstrated that networks utilizing the Gaussian clustering approach achieve 10–20% longer lifetimes than conventional mesh or torus-based topologies [22]. This improvement arises because Gaussian models maintain balanced load distribution among nodes, thereby reducing the likelihood of early energy exhaustion. Furthermore, this method effectively minimizes packet loss, latency, and reconfiguration overhead due to its probabilistic cluster boundaries, which enable nodes near cluster edges to dynamically switch associations without interrupting communication [23]. As a result, the network remains self-adaptive, resilient, and energy-efficient even in large-scale or unstable environments [24]. Table 4 presents a comparative overview of Gaussian Clustering Models against traditional mesh and torus topologies in Wireless Sensor Networks. The Gaussian model demonstrates superior energy efficiency, scalability, and load balance by incorporating probabilistic clustering and adaptive connectivity mechanisms. Unlike deterministic structures, it minimizes packet loss and enhances network lifetime by intelligently managing node communication and resource distribution.

Table 4. Comparative Analysis of Gaussian Clustering vs. Traditional Topologies in WSNs

Parameter	Mesh Topology	Torus Topology	Gaussian Clustering Model
Cluster Formation	Deterministic, fixed paths	Semi-flexible with looped boundaries	Probabilistic, based on Gaussian distribution
Energy Efficiency	Moderate; frequent retransmissions	Improved; reduced edge loss	High; adaptive clustering minimizes energy use
Load Distribution	Uneven; edge node overload	Balanced due to boundary links	Highly balanced due to probabilistic clustering
Scalability	Limited under large node densities	Moderate scalability	Excellent scalability with adaptive parameters
Packet Loss & Latency	Higher due to congestion and rerouting	Moderate; requires symmetry maintenance	Very low; adaptive links ensure stability
Network Lifetime	Shorter due to high energy usage	Moderate improvement	10–20% longer than mesh and torus networks

Gaussian connection models inherently avoid the edge congestion and hard-boundary challenges of mesh and torus, and offer truly scalable, energy-efficient clustering—even as the number of nodes or traffic load grows [25]. Probabilistic, adaptive formation is ideal for bio-inspired algorithms; it allows continuous refinement and adjustment of clusters and communication paths with minimal global coordination [26]. In simulations and deployment studies, networks with Gaussian connection models consistently exhibited lower average energy consumption, higher mean node lifetime, superior adaptability, and better tolerance to packet loss and DoS attacks [27]. For algorithms like LEGN and TEGN, Gaussian-based models enable fine-grained, data-driven decisions that maximize network efficiency, with load balancing and routing optimized through statistically derived, local operations.

V. CONCLUSION

A holistic evaluation of network topologies clearly demonstrates the superiority of Gaussian connection models for next-generation Wireless Sensor Networks (WSNs), especially when integrated with bio-inspired algorithms such as LEGN and TEGN. Unlike traditional mesh and torus topologies, Gaussian models employ probabilistic and adaptive clustering mechanisms that effectively address common challenges such as edge congestion, boundary effects, and uneven load distribution. This adaptive approach allows the network to continuously refine cluster formation and communication paths based on real-time conditions, ensuring balanced energy consumption and robust fault tolerance. As a result, Gaussian-based networks achieve significantly longer lifetimes, reduced packet loss, and lower latency compared to deterministic models. Furthermore, their statistical, data-driven cluster head selection ensures optimal routing efficiency and sustainable operation under dynamic network conditions. These advantages make Gaussian connection models a highly effective and scalable choice for modern WSN deployments, justifying their preference over mesh and torus structures in energy-efficient and resilient networking applications.

VI. FUTURE ENHANCEMENT

Future advancements in Wireless Sensor Networks (WSNs) can include integrating hybrid connection models that combine Gaussian connection mechanisms with other adaptive techniques such as small-world networks or fuzzy logic-based clustering. This integration would leverage the strengths of multiple models, enhancing connectivity, adaptability, and fault tolerance, while overcoming the limitations of single-model approaches to provide greater scalability and energy efficiency.

Enhancing bio-inspired algorithms like LEGN and TEGN with deeper reinforcement learning optimization would enable these algorithms to learn optimal clustering and routing strategies through continuous interaction with the network environment. This improvement would lead to better network longevity, adaptability, and resilience under dynamic conditions.

Expanding large-scale empirical validation through deployment in real-world WSN environments, such as smart cities, industrial IoT, and environmental monitoring, would further verify the advantages of Gaussian and hybrid models, refine their performance, and ensure their applicability under practical constraints.

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