Performance Enhancement of Wireless Sensor Networks Using a Multi-Channel Gaussian Mixture Model

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***Abstract*— Wireless Sensor Networks (WSNs) often suffer from performance degradation caused by high delay and data loss, especially in dense communication scenarios. To address these issues, this study proposes an enhanced routing protocol by integrating the Low Energy Adaptive Clustering Hierarchy (LEACH) with a Multi-Channel Gaussian Mixture Model (GMM). The LEACH protocol provides energy-efficient clustering, while GMM enables probabilistic multi-channel assignment to minimize interference and optimize packet transmission. This combined approach offers a more adaptive and data-driven mechanism for cluster formation and channel selection. Simulation results demonstrate notable improvements. The delay decreases from approximately 3.95×10^{-3} to 1.5×10^{-3} seconds, while packet loss is reduced from 0.55 to 0.40 before stabilizing at 0.56. Throughput performance also shows enhancement, rising from 125 kbps to 155 kbps after the proposed optimization. These outcomes indicate that the LEACH–GMM integration provides better communication reliability and efficiency compared to conventional LEACH, the findings highlight the potential of probabilistic multi-channel modeling for improving WSNs performance and offer a promising direction for intelligent and adaptive routing protocols in next-generation sensor networks.**

Keywords*— *Wireless Sensor Networks, LEACH, GMM, Hybrid Algorithm, Performance.

I. Introduction

Wireless Sensor Networks (WSNs) hold a pivotal role in applications such as environmental monitoring, precision agriculture, and industrial automation. Nonetheless, its communication performance frequently deteriorates under dense deployments and dynamic traffic scenarios. Recent investigations demonstrate that packet-level congestion, especially at cluster-head nodes and over shared communication channels, substantially elevates end-to-end delay and packet loss rates when numerous sensor nodes transmit concurrently [1]. Moreover, fluctuations in link quality and node contention contribute to significant jitter, undermining the stability of time-sensitive sensing tasks in real-world WSNs [2][3]. Although recent advances in low-power sensor hardware and communication protocols have improved energy efficiency, meeting stringent Quality of Service (QoS) demands, including low latency, high reliability, and consistent throughput, remains a challenge in large-scale WSNs deployments [4][5]. These persistent performance issues underline the need for routing and channel-allocation mechanisms that can more effectively manage interference, adapt to changing network conditions, and maintain robust communication in next-generation sensor networks.

To address the persistent limitations of single-channel communication[6] and sub-optimal cluster formation in large-scale Wireless Sensor Networks (WSNs)[7], recent studies have explored Multi-Channel Clustering Hierarchy (MCCH), a hybrid method that integrates the energy-efficient cluster-head rotation mechanism of LEACH with the structural robustness of Hierarchical Agglomerative Clustering (HAC). By combining LEACH's adaptive cluster-head election with HAC's topology-aware hierarchical grouping, the MCCH approach enables more balanced cluster structures and distributes nodes across multiple communication channels, thereby reducing collision, lowering end-to-end delay, and significantly improving throughput performance in dense WSNs deployments[8]. Building upon the baseline Multi-Channel Clustering Hierarchy (MCCH), this study further enhances the protocol by introducing an odd-even scheduling mechanism to regulate data transmission across clustered sensor nodes. The integration of odd-even slot allocation enables more orderly channel access, minimizes simultaneous transmissions within adjacent clusters, and reduces contention on shared links.

This improved MCCH design promotes more stable cluster communication, decreases packet collision, and ultimately elevates throughput and overall network performance in dense Wireless Sensor Networks [9]. Recent work on LEACH and its successors has explored several directions, including more selective cluster-head election schemes, adaptive thresholds, and a variety of hybrid optimization techniques designed to improve energy distribution and prolong network lifetime [10]. Research on multi-channel operation in WSNs has likewise advanced, with studies examining how traffic can be spread across orthogonal channels to ease contention and stabilize network throughput in dense settings [11]. Alongside these developments, probabilistic models such as Gaussian Mixture Models (GMMs) have been applied in wireless communications for tasks like channel estimation and prediction because they capture complex channel statistics more flexibly than deterministic approaches [12][13]. Even so, most LEACH-based routing improvements continue to separate clustering from channel selection, relying on heuristic or fixed strategies that overlook the statistical behavior of the wireless medium

[14]. This disconnection provides the rationale for the proposed MCGMM framework, which incorporates GMM-based channel characterization directly into the LEACH clustering routine to support more adaptive multi-channel decision-making.

The methodological position of the study emerges between two research streams: energy-aware clustering protocols and adaptive multi-channel assignment techniques for WSNs. Although LEACH variants have undergone extensive refinement to improve node longevity and energy distribution, recent technical surveys highlight that such protocols generally lack mechanisms capable of interpreting statistical channel variations [15]. Conversely, multi-channel studies published in the past five years frequently address contention reduction and throughput enhancement but do not embed channel selection within clustering logic [16][17]. The MCGMM framework integrates a Gaussian Mixture Model into the LEACH hierarchy so that clustering and channel allocation operate under a consistent probabilistic model. Through this configuration, the protocol occupies a distinct position in WSNs routing research by bridging hierarchical topology management with statistically informed channel utilization.

The LEACH–GMM approach offers a set of advantages that address limitations in both clustering and channel allocation within WSNs. Earlier LEACH improvements concentrate on extending lifetime through better cluster-head selection, yet they still operate over a single communication channel, making the network prone to congestion and losses as node density increases. The use of a Gaussian Mixture Model extends the routing process with a statistical representation of wireless channel trajectories, supporting channel decisions based on inferred probability distributions rather than fixed heuristics. When integrated into the LEACH hierarchy, this probabilistic mechanism reduces interference and promotes steadier packet transmission, supporting better throughput and lower delay in demanding WSNs scenarios.

II. Theoretical Framework

A. LEACH Protocol

The Low Energy Adaptive Clustering Hierarchy (LEACH) protocol operates based on a probabilistic cluster-heads (CHs) selection mechanism designed to balance the energy consumption of sensor nodes throughout the network lifetime [14][18]. A node becomes a cluster head in a given round based on a threshold function that depends on the desired percentage of CHs and the node's participation history.

The threshold T(n) for a node n is defined as:

$$T(n) = \begin{cases} \frac{P}{1-P\left(r \bmod \frac{1}{P}\right)}, & n \in G, \\ 0, & n \notin G, \end{cases} \quad (1)$$

where P is the desired proportion of cluster-heads, r is the current round number, and G is the set of nodes that have not served as CHs in the last 1/p rounds.

The probability that a node becomes a cluster head in round r is therefore determined by the value of $T(n)$, ensuring that the number of CHs remains approximately constant across rounds. Energy consumption for a transmitting node over a distance d d is commonly modeled using a first-order radio energy model:

$$E_{tx}(k,d) = \begin{cases} kE_{elec} + k\varepsilon_{fs}d^2, & d < d_0, \\ kE_{elec} + k\varepsilon_{mp}d^4, & d \geq d_0, \end{cases} \quad (2)$$

where k is the packet size in bits, E_{elec} is the electronic energy per bit, ε_{fs} and ε_{mp} denote the amplifier energies for free-space and multipath models, respectively, d_0 is the threshold distance separating the two propagation regimes.

B. GMM Protocol

A Gaussian Mixture Model (GMM) provides a probabilistic description of complex, multimodal data distributions[19][20]. In the context of wireless communication channels, GMMs are employed to model channel-state variations and to support probabilistic inference for channel selection.

A GMM with K mixture components is defined by the probability density function (PDF):

$$p(x) = \sum_{k=1}^{K} \pi_k \mathrm{N}(x \mid \mu_k, \Sigma_k), \quad (3)$$

where π_k is the mixing coefficient for component k, μ_k is the mean vector, Σ_k is the covariance matrix, $N(x \mid \mu_k, \Sigma_k)$ denotes a multivariate Gaussian distribution. The posterior responsibility of component k for an observation x is:

$$\gamma k(x) = \frac{\pi_k \mathrm{N}(x|\mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j \mathrm{N}(x|\mu_j, \Sigma_j)}, \quad (4)$$

These responsibilities form the basis for probabilistic decision-making. For channel prediction or channel-state inference, the expected value conditioned on observation y is expressed as:

$$x = \sum_{k=1}^{K} \gamma_k(y) \mathrm{E}[x \mid y, k], \quad (5)$$

given the conditional Gaussian structure, the posterior expectation for component k is computable in closed form via:

$$\mathrm{E}[x \mid y, k] = \mu_{k|k} + \Sigma_{xy|k}\Sigma_{yy|k}^{-1}(y - \mu_{y|k}) \quad (6)$$

where $\Sigma_{xy|k}$ is the cross-covariance matrix between the prediction and observation intervals, and $\Sigma_{yy|k}$ is the covariance of the observation interval. This formulation allows channel allocation in WSNs to be guided by probabilistic inference rather than deterministic heuristics, enabling adaptive multi-channel selection under dynamic network conditions.

III. Proposed MCGMM Protocol

This study proposes a routing protocol referred to as MCGMM, which enhances the conventional LEACH protocol by incorporating probabilistic multi-channel channel-state modeling based on a Gaussian Mixture Model. The primary objective of this integration is to improve communication reliability and efficiency in Wireless Sensor Networks by enabling routing decisions to adapt to dynamic channel conditions. In contrast to traditional LEACH, which relies on single-channel communication and heuristic decision making, the proposed protocol introduces statistical inference into both the clustering and communication processes.

The operation of MCGMM is organized into two main phases, namely cluster formation and probabilistic multi-channel communication. During the cluster formation phase, cluster heads are elected using the standard LEACH threshold mechanism in order to maintain balanced energy consumption among sensor nodes. After cluster-head election, the remaining nodes associate with the nearest cluster head, thereby forming a hierarchical network structure. This process preserves the energy-efficient characteristics of LEACH while providing a foundation for adaptive channel selection.

Figure 1 illustrates the overall operational flow of the proposed protocol. Once clusters are established, each cluster head performs channel-state sampling to collect information related to the quality of the available communication channels. The collected samples are subsequently processed by the GMM-based inference module, which models the statistical characteristics of channel conditions. Based on the inferred posterior probabilities, communication channels with higher likelihoods of successful transmission are selected. The selected channel is then integrated into a TDMA-based scheduling scheme to coordinate transmissions among cluster members and reduce packet collisions. Data transmission is carried out using the selected channel, completing one communication round before the protocol proceeds to the next iteration.

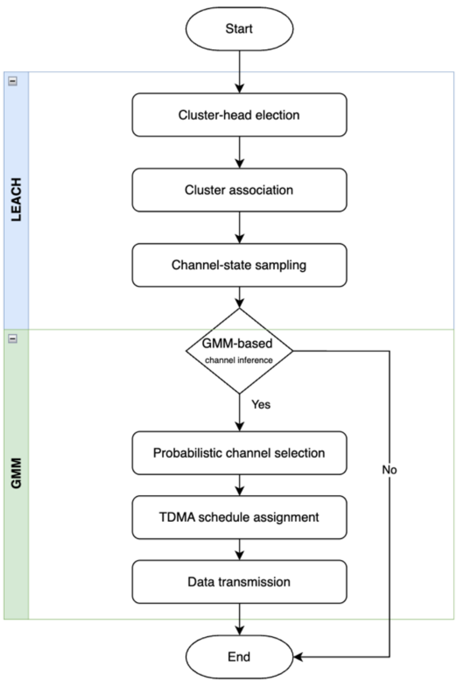

Fig. 1. Flowchart of MCGMM protocol

In the proposed MCGMM framework, the Gaussian Mixture Model is employed to represent the statistical behavior of wireless channels using locally observed channel features. Each cluster head collects channel-state samples during the sampling phase, including received signal strength indicator values and recent packet success ratios measured over short observation intervals. These features provide a concise representation of channel reliability and interference conditions. The extracted channel features are used as input to the GMM in order to estimate the posterior probability of successful transmission for each available channel. Channels with higher posterior probabilities are prioritized during the channel selection process. By relying on statistical inference rather than instantaneous measurements, the GMM is able to capture short-term channel variations while maintaining adaptive channel allocation. This design enables channel selection to be integrated directly into the LEACH hierarchy, allowing clustering and communication decisions to operate within a unified probabilistic framework.

IV. Result and Discussion

This section presents and discusses the results obtained from the performance evaluation of the proposed MCGMM protocol. The evaluation focuses on three Quality of Service (QoS) metrics that are commonly used to assess routing performance in WSNs, namely end-to-end delay, packet loss, and throughput. The results are illustrated in Figures 2 to 4 and summarized in Table 1 in order to compare the performance of MCGMM with that of the conventional LEACH protocol under identical simulation conditions.

A. Simulation Setup and Parameters

The performance of the proposed protocol was evaluated through simulation in order to provide a controlled and repeatable experimental setting. A wireless sensor network composed of N sensor nodes was randomly deployed within a square sensing area, while the base station was positioned at a fixed location. All nodes were initialized with equal energy and operated using a TDMA-based medium access control mechanism in accordance with the LEACH communication model. Data traffic followed a periodic reporting scheme, and each simulation round encompassed the processes of cluster formation, channel inference, and data transmission. To limit the influence of randomness, each configuration was simulated over several independent runs, and average performance values were reported. Four orthogonal communication channels were available to support multi-channel operation. Delay, packet loss, and throughput were measured at the sink node, and the corresponding simulation parameters are summarized in Table 1.

Table 1. Simulation parameters

Parameter	Value	Description
Number of sensor nodes (N)	100	Common LEACH network size
Deployment area	100 m × 100 m	Standard clustered WSN field
Base station location	Fixed (outside sensing area)	Long-range sink communication
Initial energy per node	0.5 J	Typical LEACH initialization
Communication channels	4	Multi-channel evaluation
MAC protocol	TDMA	LEACH-consistent MAC
Traffic model	Periodic data reporting	One packet per round
Packet size	4000 bits	Standard WSN packet
Channel features for GMM	RSSI, packet success ratio	Channel quality indicators
GMM inference location	Cluster head (CH)	Localized decision making
Number of simulation runs	20	Averaged results
Performance metrics	Delay, packet loss, throughput	Sink-based QoS metrics

B. Delay Performance

Figure 2 shows the end-to-end delay observed across the evaluated communication channels. The results indicate that delay increases from Channel 1 to Channel 2, reaching its highest value at Channel 2. This behavior suggests that Channel 2 experiences higher contention or less favorable channel conditions, which leads to increased queuing time and retransmission overhead. Such effects are typical in clustered wireless sensor networks when channel quality deteriorates due to interference or traffic concentration.

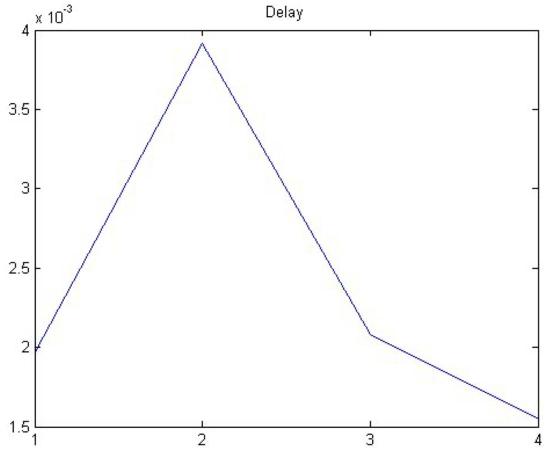

Fig. 2. Delay performance

After the application of GMM-based channel inference, a noticeable reduction in delay is observed for Channels 3 and 4, with the lowest delay recorded at Channel 4. This reduction indicates that probabilistic channel selection enables the protocol to avoid channels with unfavorable statistical characteristics. By selecting channels that offer higher transmission reliability, the proposed MCGMM protocol reduces access latency and retransmission frequency. Compared with the conventional LEACH protocol, the proposed approach achieves a delay reduction of up to 62%, demonstrating improved temporal efficiency under dynamic channel conditions.

C. Packet Loss Performance

The packet loss behavior across different channels is illustrated in Figure 3. Packet loss decreases from Channel 1 to Channel 2, reaching its minimum value at Channel 2. This reduction indicates that the GMM successfully identifies a channel with relatively stable transmission conditions during the early inference stage, resulting in improved packet delivery reliability.

However, packet loss increases gradually in Channels 3 and 4. This trend reflects the inherent dynamics of multi-channel wireless environments, where channel reuse and traffic redistribution can introduce additional interference. Despite this increase, the MCGMM protocol maintains lower packet loss than the baseline LEACH configuration under favorable channel conditions. In the best-case scenario, packet loss is reduced by 27.3%, highlighting the benefit of statistical channel modeling while acknowledging that packet loss cannot be completely eliminated due to environmental variability and network load.

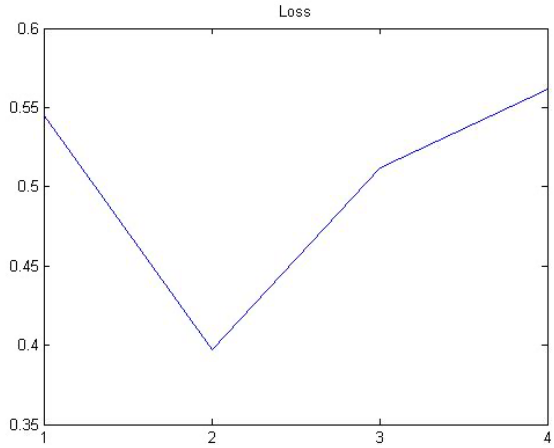

Fig. 3. Packet loss performance

D. Throughput Performance

Figure 4 presents the throughput performance across the evaluated channels. The results show a gradual decrease in throughput from Channel 1 to Channel 3, with the lowest throughput observed at Channel 3. This decrease corresponds with the increase in delay and packet loss discussed in the previous subsections, indicating reduced channel quality and higher retransmission rates.

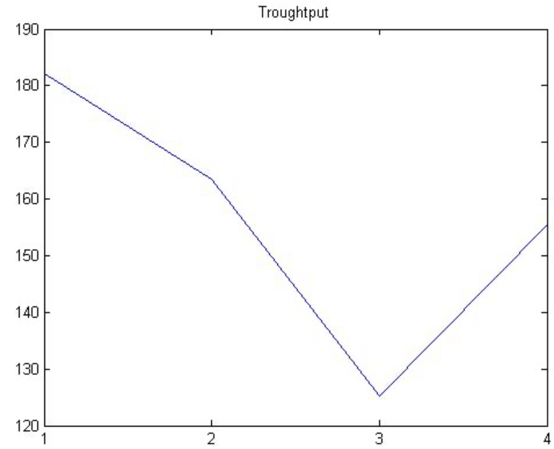

Fig. 4. Throughput performance

A recovery in throughput is observed at Channel 4, where throughput increases noticeably. This improvement confirms that the GMM-based channel reassignment mechanism is able to redirect traffic to statistically favorable channels. By reducing retransmission overhead and improving channel utilization, the proposed protocol achieves a throughput improvement of up to 34.8% compared with the conventional LEACH protocol.

E. Comparative Discussion

The comparative results summarized in Table 2 demonstrate that the proposed MCGMM protocol consistently outperforms the conventional LEACH scheme across all evaluated QoS metrics. By incorporating GMM-based channel inference into the LEACH hierarchy, the proposed protocol introduces channel awareness into the clustering process, thereby enabling routing decisions that respond to statistical variations in channel conditions. The observed improvements in delay, packet loss, and throughput collectively indicate that MCGMM provides a more adaptive and reliable routing framework for clustered wireless sensor networks.

Table 2. Performance comparison of LEACH vs MCGMM

Parameter	LEACH	MCGMM	Improvement
Delay ($\times 10^{-3}$ s)	3.95 – 4.00	1.50 – 2.00	↓ 62.0%
Packet Loss	0.55 – 0.56	0.40 – 0.56	↓ 27.3%
Throughput (kbps)	125 – 135	155 – 182	↑ 34.8%
Adaptability	Single-channel	Probabilistic multi-channel	Improved
Channel Awareness	None	GMM-based inference	Enabled

V. Conclusion

This paper presented MCGMM, an enhanced routing protocol for wireless sensor networks that extends the conventional LEACH framework through probabilistic multi-channel channel-state modeling based on a Gaussian mixture model. The main objective of this integration is to incorporate statistical channel awareness into the hierarchical routing structure. Unlike traditional LEACH, which relies on fixed or heuristic channel usage, the proposed protocol enables channel selection to adapt to changing wireless conditions. As a result, routing decisions become more responsive to channel variability commonly observed in dense sensor deployments. This design preserves the energy-efficient clustering characteristics of LEACH while improving communication flexibility.

Simulation-based evaluation shows that the proposed protocol improves overall network performance when compared with standard LEACH. Improvements are observed in delay and packet loss, indicating enhanced transmission reliability. At the same time, throughput behavior becomes more consistent across different channel conditions. These performance trends suggest that probabilistic multi-channel selection helps mitigate contention and interference effects. The results confirm that channel-aware routing can contribute to more efficient data delivery in clustered wireless sensor networks.

In summary, MCGMM provides a routing solution that improves adaptability and robustness without altering the fundamental LEACH clustering mechanism. The findings demonstrate that integrating statistical channel modeling into hierarchical routing is a viable approach for improving quality of service. Although the current study emphasizes QoS performance, energy efficiency analysis remains outside its primary scope. Future research will explore learning-based channel adaptation and energy-aware extensions to further enhance protocol effectiveness.

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