

Article

A Lightweight Hybrid Mobile Groupcasting Protocol for Spatially Heterogeneous Sink Groups in WSNs [†]

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Abstract

Efficient data dissemination to mobile sink groups with heterogeneous spatial distributions that are globally sparse but locally dense remains a critical challenge in wireless sensor networks (WSNs). To address severe energy inefficiencies in conventional single-strategy approaches, we propose an energy-efficient, strictly lightweight hybrid mobile groupcasting protocol that dynamically integrates unicasting and partial flooding. The proposed protocol eliminates in-network computational overhead by shifting the entire subgrouping burden exclusively to the data source. The source formulates data dissemination as an analytical cost minimization problem and executes a highly scalable heuristic subgrouping algorithm that operates in linear time, $\mathcal{O}(|M|)$, relative to the number of member sinks. By embedding this optimal configuration directly into the data packet header, resource-constrained intermediate sensor nodes are completely relieved from heavy clustering calculations and only need to execute simple, predefined geographic forwarding or localized flooding rules. The simulation results using the QualNet 4.0 platform validate that our source-delegated architecture significantly reduces redundant transmissions and unnecessary flooding regions. The proposed protocol achieves up to 24% and 44.5% reductions in communication energy consumption compared to conventional unicasting-based and flooding-based protocols, respectively, while maintaining reliable data delivery under realistic network dynamics.

Keywords: wireless sensor networks; mobile groupcasting; mobile sink group; energy-efficient data dissemination; hybrid data dissemination



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1. Introduction

Wireless sensor networks (WSNs) have been widely used in a variety of applications, such as environmental monitoring, smart battlefields, home automation, and traffic control [1]. As comprehensively surveyed in [2], despite these continuous technological innovations spanning environmental and industrial applications, persistent operational constraints such as strict energy availability, unpredictable dynamic topologies, and scalable routing overheads still remain primary challenges that demand fundamental network layer optimization.

In such systems, mobile sinks can reduce network traffic by moving through the network to collect data, instead of requiring all sensor nodes to report to a static sink [3]. As a special type of mobile sink, such as a platoon of firefighters, soldiers, or vehicles in cooperative driving scenarios, the concept of a mobile sink group has been widely studied in the literature [4]. These groups are of particular interest because they exhibit unique mobility characteristics that combine both individual movement and coordinated group behavior. Mobile sinks in a mobile sink group collect sensed data while moving and share common objectives, such as missions, interests, and destinations. Specifically, each mobile sink can move freely at a local level, while the group as a whole exhibits coordinated movement toward a common destination at a global level [5]. Such mobility characteristics make efficient data dissemination to mobile sink groups a challenging problem in wireless sensor networks.

Efficient data dissemination to mobile sink groups is essential for sharing critical information, such as task instructions, hazard locations, and emergency events. However, traditional data dissemination protocols designed for single mobile sinks cannot be directly applied, as they do not consider the collective mobility of mobile sink groups and may result in significant resource inefficiency. For example, multicasting protocols [6] can be applied; however, frequent tree reconstruction caused by sink mobility leads to high energy consumption and increased transmission delay. Geocasting [7] can reduce dissemination cost and delay for mobile sink groups; however, it is effective only when sinks remain within a predefined static region. Consequently, data delivery may fail when sinks move out of the geocasting region, leading to reduced reliability. These limitations highlight the need for a data dissemination protocol that can efficiently support the collective mobility of mobile sink groups.

To address this problem, mobile groupcasting protocols [8–10] have been developed to support efficient data dissemination to mobile sink groups. These protocols maintain and periodically update the current geographical region of a mobile sink group at the data source. Based on this information, the source forwards data packets to nodes located near the mobile sink group, allowing mobile sinks to receive the data efficiently. However, these approaches typically rely on a single data dissemination strategy—either unicasting or flooding—which limits their efficiency under heterogeneous spatial distributions of sink nodes. This limitation motivates the need for a hybrid data dissemination approach that can adapt to varying spatial characteristics within a mobile sink group.

As shown in Figure 1, mobile groupcasting can be classified into two data dissemination strategies: unicasting-based mobile groupcasting [8,9] and flooding-based mobile groupcasting [10]. In unicasting-based protocols, data packets are delivered from a source to individual mobile sinks through point-to-point transmissions. Typically, a designated mobile sink (or agent) receives data packets from the source and forwards them to other sinks via multiple unicast transmissions. In flooding-based protocols, data packets are disseminated within a geographically restricted region corresponding to the mobile sink group. In this approach, mobile sinks receive data packets through controlled flooding within the group region.

From an energy efficiency perspective, unicasting-based protocols are effective for a small number of sparsely located sinks, whereas flooding-based protocols are more effective when sinks are densely distributed. However, in practical scenarios, mobile sinks are typically distributed in a heterogeneous manner, where the mobile sink group is globally sparse but locally dense. In such environments, neither unicasting nor flooding can efficiently support data dissemination, as both approaches may result in significant energy waste. For example, as illustrated in the sparse distribution scenario of Figure 1, unicasting-based protocols incur redundant transmissions when delivering data to densely located sinks,

leading to unnecessary energy consumption. On the other hand, as illustrated in the dense distribution scenario of Figure 1, flooding-based protocols generate unnecessary flooding regions due to a small number of sparsely located sinks, resulting in excessive energy consumption. This limitation becomes even more pronounced in dynamic and practical scenarios where mobile sink groups frequently merge or split. These observations indicate the necessity of a hybrid data dissemination approach that can adapt to heterogeneous spatial distributions within a mobile sink group.

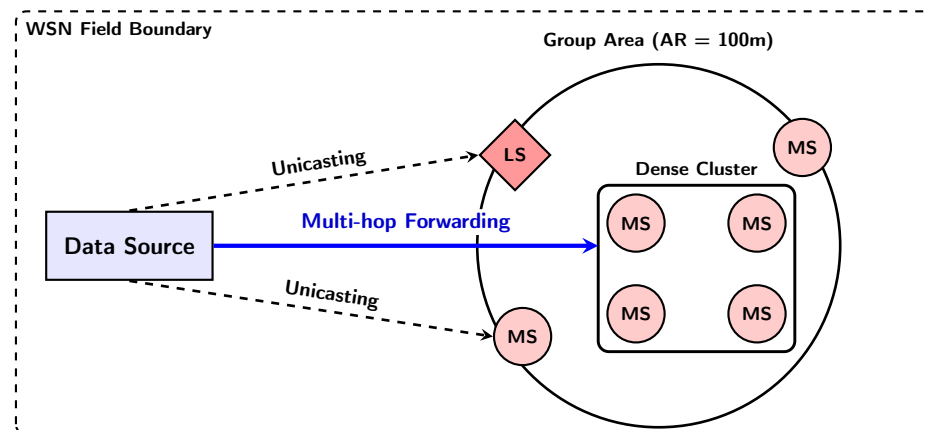


Figure 1. Illustration of the spatial heterogeneity challenge and the proposed hybrid routing approach in WSNs.

In this paper, we propose an energy-efficient mobile groupcasting protocol that adaptively combines partial flooding for densely located sinks and unicasting for sparsely located sinks within a mobile sink group. By eliminating unnecessary flooding regions caused by a small number of sparsely located sinks, the proposed protocol significantly reduces communication overhead. However, determining the optimal number of flooding subgroups is computationally expensive, particularly in resource-constrained sensor networks. To address this challenge, we adopt a simplified subgrouping strategy that divides a mobile sink group into a single flooding subgroup and a unicasting subgroup. This design is based on the observation that unnecessary data dissemination is often caused by a small number of sinks deviating from densely clustered regions. We further develop an analytical model to determine an optimal combination of the flooding subgroup and the unicasting subgroup. Extensive analyses and simulations demonstrate that the proposed protocol achieves significantly improved energy efficiency compared to existing protocols, including M-Geocasting [10] and Virtual Line-Based Data Dissemination (VLDD) [9]. This hybrid design enables efficient data dissemination under heterogeneous spatial distributions of mobile sink groups.

The main contributions of this paper are summarized as follows:

- **Lightweight Hybrid Groupcasting Framework:** We propose a novel, highly adaptive data dissemination framework that dynamically integrates unicasting and partial flooding. By evaluating real-time spatial density, it eliminates the structural inefficiencies of relying on a single, rigid routing mode under heterogeneous distributions.
- **Source-Delegated Computation with Linear Complexity:** To achieve strictly lightweight operations in resource-constrained networks, the proposed protocol completely offloads the combinatorial subgrouping optimization from intermediate sensor nodes to the data source. The source solves the cost minimization problem using a practical heuristic algorithm that reduces the theoretical search space to a linear time complexity of $\mathcal{O}(|M|)$ relative to the number of member sinks, requiring only a few milliseconds of execution time.

- **Header-Driven In-Network Forwarding with Zero State Overhead:** By embedding the computed optimal subgrouping configuration directly into the data packet header, intermediate sensor nodes are entirely relieved from running dynamic clustering or maintaining routing state tables. Sensor nodes simply parse the header and execute predefined, simple geographic forwarding or localized flooding, minimizing both control overhead and collision risks.
- **Rigorous Performance Validation under Realistic MAC Dynamics:** Through extensive simulations on the QualNet 4.0 platform [11] using validated IEEE 802.15.4 [12] MAC and physical layer models, we demonstrate that the proposed protocol significantly outperforms state-of-the-art baselines. It achieves up to 24% and 44.5% energy reductions compared to unicasting-based and flooding-based protocols, respectively, while maintaining high delivery resilience despite packet collisions and interference.

The remainder of this paper is organized as follows: Section 2 reviews related work. Section 3 presents the proposed protocol and its underlying analytical model. Section 4 evaluates the performance of the proposed protocol through analytical and simulation-based evaluations. Finally, Section 5 provides concluding remarks.

2. Related Works

2.1. Data Dissemination for Mobile Sinks

In wireless sensor networks, early data dissemination protocols were primarily designed for static sinks or focused heavily on real-time delivery guarantees. Foundational spatiotemporal protocols like SPEED [13] established the basis for soft real-time communication. Subsequent studies have extended this approach to address various challenges, including energy-aware routing [14,15], probabilistic multi-path forwarding for reliability [16,17], multi-hop velocity mechanisms [18,19], and fault tolerance using void bypass schemes [20] or neural networks [21]. However, as mobile sinks were introduced to reduce the energy consumption of sensor nodes near the static sink, location service schemes [22] and routing protocols handling individual sink mobility gained attention.

To address these early layout limits, various algorithmic approaches have been formulated to achieve both reliable data delivery and structural efficiency. For instance, an efficient data dissemination paradigm [23] was developed to establish stable routing configurations under dynamic node states, attempting to balance transmission reliability against overall energy consumption in fundamental WSN environments.

In the context of supporting multiple target nodes, traditional multicasting protocols [6] have frequently been adapted to deliver data to multiple mobile sinks. However, these protocols encounter severe energy inefficiencies in mobile scenarios because sink movement continuously disrupts the established routing structure, leading to frequent and resource-heavy multicast tree reconstructions that prolong transmission delays. To mitigate this dynamic maintenance overhead, geocasting protocols [7] provide an alternative by discarding strict tree structures and instead establishing a targeted data dissemination process directed at a specific geographical region. Nevertheless, conventional geocasting approaches are fundamentally restricted to static, predefined target areas. When mobile sinks actively move beyond the boundaries of the designated geocasting zone, the protocol suffers from severe data delivery failures, drastically reducing reliability. These detailed architectural limitations demonstrate that conventional routing strategies tailored for individual mobility or static localized areas are highly inadequate for handling the complex spatiotemporal dynamics and collective mobility of mobile sink groups.

To suppress redundant packet duplications in such geocasting paradigms, grid-based regional partitioning strategies have garnered significant attention. For instance, an efficient grid-based geocasting scheme [24] restricts flooding actions purely within a localized grid

structure matching the target region, which effectively minimizes multi-hop propagation metrics but introduces a geometric localization dependence under rapid sink movements.

2.2. Mobile Groupcasting Protocols

To address the collective mobility, mobile groupcasting protocols have been proposed, which track the geographical region of a mobile sink group and forward data accordingly. These protocols are generally classified into two categories: unicasting-based and flooding-based strategies.

Unicasting-based protocols, such as GrLS [8] and VLDD [9], rely on point-to-point transmissions. For instance, VLDD builds a virtual line to forward data, and an agent node sequentially sends the data to individual member sinks. While effective for a small number of scattered sinks, this approach incurs significant redundant transmissions and energy waste when sinks are densely clustered.

Conversely, flooding-based protocols like M-Geocasting [10] define a restricted geographical area corresponding to the sink group and flood the data within that region. This strategy is highly reliable and efficient for dense regions. However, when a small number of sinks deviate from the cluster, the flooding boundary must be excessively expanded, causing unnecessary broadcast storms and severe energy depletion.

2.3. Advanced WSN Scaling and Routing Mechanisms

Beyond basic mobile sink routing, various advanced scaling methods have dominated the WSN literature in recent years to optimize energy and reliability. We categorize these into five main approaches: First, hierarchical clustering protocols, such as LEACH, HEED, and TEEN [25,26], effectively reduce the energy load through data aggregation and cluster leader rotation. However, dynamic cluster reformation incurs significant control overhead, which our source-delegated subgrouping explicitly aims to avoid. Second, geographic zone-based protocols, such as GEAR and ZBR [27], dynamically limit transmission areas without requiring full network flooding. This concept shares similarities with our partial flooding approach but is typically optimized for static regional events rather than dynamically moving sink groups. Third, methods based on planar-geographic graphs, including Greedy Perimeter Stateless Routing (GPSR) with various void-handling optimizations [28], provide highly scalable forwarding in large networks. While our protocol leverages foundational geographic routing for unicasting, it supplements it with a hybrid groupcasting mechanism to efficiently handle dense sink clusters. Fourth, solutions based on mobility prediction, employing Markov chains, Gauss-Markov models, or learning-based algorithms [29,30], effectively reduce the number of required sink location updates by predicting future trajectories. Finally, opportunistic routing protocols, such as ExOR and MORE [31], improve reliability and scalability in highly dynamic topologies by exploiting the broadcast nature of the wireless medium.

Furthermore, routing optimization becomes significantly more challenging when data generation across sensor fields is inherently non-uniform. To handle such asymmetry, an optimal clustering and link construction mechanism driven by mobile sinks [32] was recently proposed to adaptively manage non-uniform data collection domains, extending the network lifetime through cost-function balance at specific rendezvous points.

While these diverse methods significantly enhance WSN scalability, directly applying them to spatially heterogeneous mobile sink groups often introduces prohibitive computational or state-maintenance overheads for intermediate sensor nodes. Thus, our proposed protocol focuses on a strictly lightweight, hybrid dissemination strategy.

2.4. Limitations of Existing Approaches

The fundamental limitation of existing mobile groupcasting protocols lies in their reliance on a single, uniform data dissemination strategy. In practical scenarios, the spatial distribution of a mobile sink group is highly dynamic and heterogeneous, often globally sparse but locally dense. Under such distributions, applying only unicasting leads to heavy overlapping paths in dense areas, whereas applying only flooding causes an unnecessary over-allocation of network resources for a few outlier sinks.

Moreover, attempting to address this spatial heterogeneity through complex dynamic clustering algorithms introduces prohibitive computational overhead. In resource-constrained WSNs, the energy consumed by calculating optimal multi-cluster formations and exchanging control packets often outweighs the energy saved in data transmission. While recent advancements have explored machine learning or Unmanned Aerial Vehicle (UAV)-assisted routing for dynamic networks [33–35], these sophisticated approaches require substantial processing power and are typically unsuitable for traditional, severely constrained sensor nodes. Therefore, there is a critical need for a lightweight, adaptive hybrid data dissemination approach. Such a protocol must intelligently partition the group and apply the most energy-efficient routing mode (i.e., partial flooding or unicasting) based on real-time spatial characteristics, while keeping the subgrouping heuristic computationally simple to truly preserve battery life.

We explicitly acknowledge that modern ML and UAV-assisted routing mechanisms [33–35] exhibit outstanding energy efficiency during actual packet delivery, primarily through intelligent data aggregation, optimized trajectory planning, and model simplification techniques (e.g., localized neural network pruning). However, their implementation inherently requires specialized hardware or intensive computation on sensor nodes during deployment. This limits the spectrum of comparison because our target environment strictly comprises standard, resource-constrained nodes (such as MICA2) that cannot sustain complex execution loops. By expanding our structural comparison to encompass traditional hierarchical clustering, zone-based routing, and modern ML/UAV optimizations in Table 1, we provide a more comprehensive overview of the existing WSN scaling domain.

Table 1. Comparison of the proposed protocol with various WSN scaling and groupcasting approaches.

Protocol/ Class	Strategy	Computational Overhead	Algorithmic Complexity	Adaptability to Heterogeneity	Key Limitations
VLDD [9]	Unicasting	Low	$\mathcal{O}(M)$	Poor	Redundant transmissions in dense areas
M-Geocasting [10]	Flooding	Low	$\mathcal{O}(N)$	Poor	Unnecessary flooding in sparse areas
LEACH [25]	Hierarchical	Medium to High	$\mathcal{O}(N)$	Fair	Dynamic cluster leader rotation overhead
GEAR [27]	Regional	Medium	$\mathcal{O}(N)$	Fair	Limited to static target regions
ML/UAV [33–35]	Optimization	High	$\mathcal{O}(N^2)$	Good	Prohibitive processing on sensor nodes
Proposed Protocol	Hybrid	Low	$\mathcal{O}(M)$	Excellent	Simplified single-flooding heuristic

3. The Proposed Protocol

3.1. System Model and Network Initialization

We consider a wireless sensor network in which a large number of sensor nodes are deployed in a sensor field. Each mobile sink collects data from nearby sensor nodes and communicates with other mobile sinks through multi-hop communication via sensor nodes, without relying on external infrastructure such as the Internet or 3G/LTE networks. A mobile sink group moves collectively toward a common destination, while each member can move independently within a limited range. The allowable movement range is

predefined by applications, and we denote AR as the radius of the mobile sink group. Each mobile sink is assigned a unique group ID and sink ID . Each mobile sink group consists of a designated Leader Sink (LS) and multiple Member Sinks (MSs). The LS is responsible for collecting location information from MSs to estimate the current position of the mobile sink group. We assume that all sensor nodes and mobile sinks are aware of their own location information through GPS devices or other localization schemes [22]. Under this assumption, geographic routing protocols such as GPSR [28] are employed as the underlying communication protocol.

The proposed subgrouping algorithm determines an optimal partition of a mobile sink group into a flooding subgroup and a unicasting subgroup. Given a set of member sinks, the algorithm evaluates all possible subgroup combinations and computes the total data dissemination cost for each configuration using the defined cost functions. For each candidate subgroup, the flooding cost and unicasting cost are calculated, and the configuration with the minimum total cost is selected as the optimal solution. This process provides a basis for balancing flooding and unicasting based on the spatial distribution of sinks, thereby improving overall energy efficiency. While the algorithm provides the optimal solution, note that the above procedure considers all possible subgroup combinations to determine the minimum-cost configuration. Although this exhaustive search introduces computational overhead, in practical implementations, the proposed protocol employs a simplified heuristic that considers a single flooding subgroup and a unicasting subgroup. This distinction ensures that the analytical model remains tractable while the practical protocol maintains low computational complexity.

To clarify how these mathematical formulations materialize into a highly energy-efficient and lightweight routing operation, the overall implementation flow is structured into three concrete operational phases: (1) Source-Delegated Subgrouping: The data source independently executes Algorithm 1 using the linear-time $\mathcal{O}(|M|)$ heuristic to solve the cost minimization problem defined in Equation (3). This architecture ensures that all heavy combinatorial calculations are confined to the source, leaving intermediate sensor nodes entirely untouched by computational overhead. (2) Header-Embedded Configuration: The optimal partitioning result (i.e., specifying which member sinks belong to the flooding subgroup or the unicasting subgroup, alongside spatial parameters C_{sf} and R_{sf}) is directly encoded into the data packet header. (3) Stateless In-Network Forwarding: Intermediate sensor nodes simply parse this routing header and execute predefined, localized forwarding rules (e.g., standard geographic routing toward unicast sinks or localized broadcast within R_{sf}). Because nodes perform zero runtime optimization or topology maintenance, energy consumption is strictly optimized for data delivery rather than control and computing overhead.

Algorithm 1 Subgroup Selection for Hybrid Dissemination

Require: M : set of member sinks, $Cost_f(\cdot)$: flooding cost function, $Cost_u(\cdot)$: unicasting cost function

Ensure: $FGroup$: flooding subgroup, $UGroup$: unicasting subgroup

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1:  $minCost \leftarrow \infty$ 
2:  $bestFGroup \leftarrow \emptyset$ 
3: for all subsets  $S \subseteq M$  do
4:    $FGroup \leftarrow S$ 
5:    $UGroup \leftarrow M \setminus S$ 
6:    $C \leftarrow Cost_f(FGroup) + Cost_u(UGroup)$ 
7:   if  $C < minCost$  then
8:      $minCost \leftarrow C$ 
9:      $bestFGroup \leftarrow FGroup$ 
10:  end if
11: end for
12: return ( $bestFGroup, M \setminus bestFGroup$ )

```

We assume that sensor nodes remain stationary after deployment and are uniformly distributed over the sensor field. Each sensor node has limited energy resources and communicates with neighboring nodes within its transmission range. We further assume that communication between nodes is assumed to be reliable within the transmission range for simplicity, and multi-hop routing is used for long-distance data dissemination. In this model, the group radius AR defines the spatial extent of a mobile sink group and will be used in subsequent procedures for region construction and data dissemination.

To enhance the readability of the analytical models and protocol descriptions, the key mathematical notations and physical quantities used in this paper are summarized in Table 2.

Table 2. Summary of key notations.

Notation	Description
M	Set of all member sinks in a mobile sink group
LS, MS	Leader Sink and Member Sink
AR	Allowable movement radius of the mobile sink group
SC, SR, SA	Center point, radius, and region of the Search Area
CC, CR, CA	Center point, radius, and region of the Current Area
C_{sf}, R_{sf}	Center point and radius of the flooding subgroup
N_f	The first intermediate sensor node within CA receiving the packet
$Cost_f(\cdot)$	Estimated communication cost for partial flooding
$Cost_u(\cdot)$	Estimated communication cost for unicasting
$Cost_{total}$	Total data dissemination cost for a subgroup configuration
TRR	Transmission range of sensor nodes

3.2. Obtaining the Location Information of the Group

The LS selects a neighboring sensor node as an agent node, which initiates a flooding process by broadcasting a member search message within a predefined search area. The search area (SA) is defined as a circular region centered at SC , which corresponds to the current position of the LS , with a radius $SR = 2 \times AR$.

Upon receiving the search message, each MS sends an acknowledgment message containing its current position to the agent node. The agent node then forwards the collected location information to the LS . After receiving acknowledgment messages from all MS s, the LS computes the current area (CA) that encompasses all member sinks. We assume that the LS is aware of the total number of member sinks a priori. If the LS fails to collect location information from all MS s, it incrementally expands both SA and AR to widen the search region.

To prevent repeated and ineffective broadcast searches in cases where some member sinks move completely outside the search area or experience temporary disconnection, the Leader Sink (LS) implements a strictly bounded exception handling mechanism. Specifically, the LS waits for a predefined interval (T_{wait}) to receive acknowledgment packets. If acknowledgments are still missing, the LS limits the maximum number of expanded search retries to a predefined threshold (MAX_RETRY). If the missing member sinks do not respond after reaching this limit, they are temporarily classified as disconnected and are excluded from the current location update and subgrouping cycle.

After handling these exceptions, CA is defined as a circular region centered at CC , which represents the average coordinates of all responding member sinks, with a radius $CR = AR$. This loosely defined group area improves the reliability of data dissemination to sinks located near the boundary of the mobile sink group, compared to the tightly defined regions used in previous studies. This design also enhances robustness against mobility, as it increases the likelihood that mobile sinks near the boundary remain within the dissemination region despite dynamic movement.

The *LS* then disseminates the computed *CA* to data sources. Using location service schemes, the *LS* can obtain the locations of data sources. Although the flooding-based search process introduces additional control overhead, it is performed intermittently and is limited within the search area, thereby incurring relatively low communication cost compared to data dissemination. The location information of the mobile sink group is periodically updated to reflect mobility dynamics, ensuring that data dissemination remains effective over time.

3.3. Subgrouping

Once a data source obtains the *CA* of a mobile sink group, it partitions the group into two subgroups: a flooding subgroup and a unicasting subgroup. This partitioning is determined using Algorithm 1, which selects the subgroup configuration that minimizes the total data dissemination cost.

It is crucial to understand how this mathematical formulation translates to a lightweight and highly scalable operation for mobile multicast. Although a theoretically optimal full search over all possible subset combinations yields a worst-case time complexity of $\mathcal{O}(2^{|M|})$, which restricts scalability for large groups, the proposed practical protocol completely bypasses this bottleneck. In actual network deployments, the protocol strictly employs a simplified heuristic that considers only a single flooding subgroup and a unicasting subgroup as described in Algorithm 1. By sorting member sinks based on their distances to the group center and finding a single partitioning point, the computational complexity of our practical subgrouping algorithm drops dynamically to linear time, i.e., $\mathcal{O}(|M|)$. Furthermore, this linear computation is entirely offloaded to the data source (which possesses sufficient energy and processing power), meaning that resource-constrained intermediate sensor nodes do not perform any clustering or cost calculations. Consequently, even when the number of member sinks grows significantly, the algorithm remains highly scalable and can be executed within a few milliseconds at the source, ensuring low computational overhead in practical scenarios.

To reduce computational complexity and control overhead, we restrict the subgrouping to a single flooding subgroup and a unicasting subgroup. This design is based on the observation that unnecessary data dissemination is primarily caused by a small number of sinks deviating from densely clustered regions, making a single flooding subgroup sufficient in most practical scenarios.

The source then generates data packets containing the subgrouping information along with *CC* and *CR*, and forwards them toward the group region. The data packets are forwarded toward the center point *CC* until they reach a sensor node located within the *CA*. As shown in Figure 2, the node N_f is defined as the first sensor node within the *CA* that receives the data packet. Upon receiving the packet, N_f stops forwarding toward *CC* and performs data dissemination based on the subgrouping information, applying partial flooding for the flooding subgroup and unicasting for the remaining sinks.

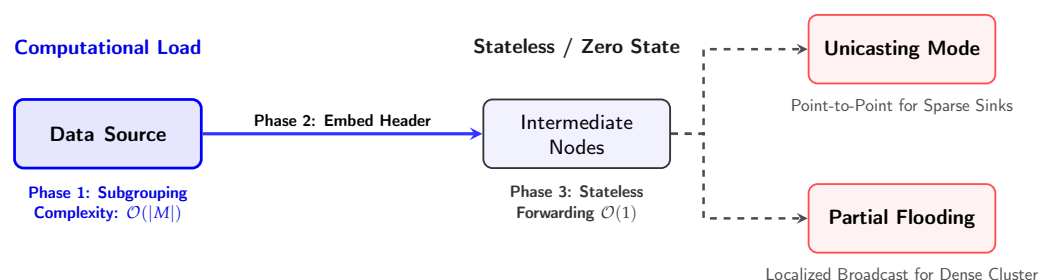


Figure 2. The three-phase execution pipeline of the proposed source-delegated framework.

For simplified analysis, we assume that N sensor nodes are uniformly distributed over a square sensor field of area A . Under this assumption, the flooding cost for a subgroup can be approximated as follows:

$$Cost_f(FGroup) = m \cdot \frac{N}{A} \cdot \pi R^2, \quad (1)$$

where m represents the size of a data packet and R denotes the radius of the flooding region.

Similarly, the unicasting cost between two nodes a and b is approximated as follows:

$$Cost_u(a, b) = m \cdot \frac{dist(a, b)}{TRR}, \quad (2)$$

where $dist(a, b)$ is the Euclidean distance between nodes a and b , and TRR denotes the transmission range of sensor nodes.

The cost models used in this study are approximate and are primarily designed to capture the relative communication overhead of flooding and unicasting at the network layer. We acknowledge that these linear and quadratic approximations do not explicitly account for data link layer dynamics, such as wireless interference, MAC-layer collisions, channel quality variations, or adaptive MAC mechanisms. While these factors are undeniably crucial for scaling in real-world WSNs, incorporating complex cross-layer metrics (e.g., non-linear interference calculations or CSMA/CA backoff modeling) into the objective function would severely increase the computational complexity of the subgrouping algorithm. Because our core objective is to evaluate the spatial routing efficiency of the hybrid groupcasting approach while maintaining strictly lightweight operations, these abstracted models provide a computationally tractable and reasonable basis for comparing relative subgroup configurations.

Evaluating the protocol's performance under highly dynamic, adaptive MAC mechanisms and exploring cross-layer optimizations are critical directions for our future work. Given a subgroup configuration, the total data dissemination cost is computed as the sum of the flooding cost for the flooding subgroup and the unicasting cost for the remaining sinks. For example, let a group $G = \{m_1, m_2, \dots, m_n\}$ be divided into a flooding subgroup $\{m_1, m_2\}$ and a unicasting subgroup $\{m_3, \dots, m_n\}$. In this case, the total cost is calculated as the sum of $Cost_f(\{m_1, m_2\})$ and the corresponding unicasting costs for $\{m_3, \dots, m_n\}$. Therefore, the subgrouping problem can be formulated as a cost minimization problem, where the objective is to determine the optimal partition that minimizes the total data dissemination cost. The optimal subgroup configuration is obtained by evaluating all possible combinations and selecting the one that minimizes the total cost.

Since the exact position of N_f is not known a priori, CC is used as a reference point to approximate the remaining distance cost from the group area to the flooding subgroup. To handle cases where the reference point is already inside the flooding region (i.e., $dist(CC, C_{sf}) < R_{sf}$), the distance cost is strictly bounded to zero using a maximum function. Accordingly, the total cost can be expressed as follows:

$$Cost_{total} = \min_{FGroup \subseteq M} \left\{ m \cdot \frac{\max(0, dist(CC, C_{sf}) - R_{sf})}{TRR} \cdot \frac{N}{A} \cdot \pi R_{sf}^2 + \sum_{m_k \in UGroup} m \cdot \frac{dist(N_f, m_k)}{TRR} \right\} \quad (3)$$

where C_{sf} and R_{sf} denote the center point and radius of the flooding subgroup, respectively. The radius R_{sf} is determined as the distance between C_{sf} and the farthest member sink

in the flooding subgroup. The summation term represents the total unicasting cost for all member sinks m_k in the unicasting subgroup ($UGroup$).

As described in Algorithm 1, the data source initializes the tracking variables where $minCost$ represents the minimum total communication overhead (set to infinity initially) and $bestFGroup$ denotes the optimal subset of mobile sinks for the flooding subgroup. For each candidate $FGroup$, the total routing cost is dynamically evaluated based on Equation (3) to find the most energy-efficient partitioning layout.

3.4. Data Dissemination

As described above, N_f , the first node within CA that receives the data packet, generates copies of the packet and forwards them separately to the flooding subgroup and the unicasting subgroup. Selecting N_f as the first node within CA minimizes the forwarding overhead from the source to the mobile sink group, enabling an efficient transition from long-distance forwarding to localized data dissemination. Accordingly, the proposed protocol operates in two routing modes: flooding mode and unicasting mode.

In flooding mode, the destination field of the packet is set to the center point of the flooding region for geographic routing. This process can be recursively applied; however, the maximum nesting depth is practically limited to two. This limitation is derived from the strict quantitative resource constraints of typical sensor nodes. For instance, in MICA2 nodes (which are utilized in our simulation model), the default maximum packet size under TinyOS is typically restricted to 36 bytes, providing a payload capacity of only 29 bytes [36]. Even in general IEEE 802.15.4-compliant sensor networks, the physical layer maximum transmission unit (MTU) is strictly limited to 127 bytes, leaving approximately 100 bytes for the MAC payload [12]. Since each nesting level requires additional geographic coordinates (i.e., center point and radius) to be embedded in the packet header, exceeding a nesting depth of two would cause the routing header size to grow excessively, leaving insufficient capacity for the actual data payload.

To handle complex hierarchical subgrouping scenarios where more than two nesting levels are theoretically required, the proposed protocol implements a straightforward fallback mechanism. Instead of discarding subsequent nesting or issuing error messages, the protocol automatically reverts to the pure unicasting mode for the remaining outlier sinks. This ensures reliable data delivery without violating the strict packet size constraints of practical WSN deployments.

In unicasting mode, data dissemination follows conventional geographic routing protocols such as [28]. The LS periodically updates the current area information and disseminates it to data sources, enabling timely data dissemination to the mobile sink group.

This hybrid routing mechanism enables the proposed protocol to efficiently handle heterogeneous spatial distributions within a mobile sink group by reducing redundant transmissions in dense regions and avoiding unnecessary flooding in sparse regions.

4. Simulation

4.1. Simulation Environments and Performance Evaluation Metrics

In this section, we first conduct an analytical evaluation of energy consumption for different data dissemination methods using MATLAB vR2019b [37]. We then evaluate the performance of the proposed protocol in terms of energy consumption and data delivery ratio, and compare it with existing protocols: VLDD [9], representing unicasting-based mobile groupcasting, and M-Geocasting [10], representing flooding-based approaches. These protocols are implemented in the QualNet 4.0 network simulator [11]. This version was specifically selected due to its highly stable and rigorously validated IEEE 802.15.4 MAC

and PHY layer models, which are essential for accurately measuring precise communication energy consumption and collisions in resource-constrained WSNs.

To ensure complete reproducibility of our evaluation, the comprehensive configuration parameters for both the network environment and protocol settings are consolidated in Table 3.

Table 3. Simulation environment configuration and protocol settings.

Configuration Parameter	Value/Setting
Simulation Platform	QualNet 4.0
Network Size	1000 m × 1000 m Square Field
Total Sensor Nodes (N)	2000 Nodes (Random Non-uniform Distribution)
Hardware Baseline Model	MICA2 Reference Specifications
Radio Transmission Range (TRR)	25 m
Tx/Rx Power Consumption	21 mW/15 mW
MAC/PHY Layer Standard	IEEE 802.15.4
Data Packet Volume (Size)	128 Bytes
Mobile Sink Group Size ($ M $)	10 Member Sinks (Default)
Group Mobility Model	Reference Point Group Mobility (RPGM) Model
Sink Mobility Speed	10 m/s (Average)
Group Radius (AR)	100 m
Exception Bounded Retries	$MAX_RETRY = 3$
Location Wait Interval (T_{wait})	2.0 s

For large-scale simulations, 2000 sensor nodes are randomly distributed over a 1000 m × 1000 m area. The sensor node model follows the specifications of MICA2 [36]. The transmission range is set to 25 m, and the power consumption rates for transmission and reception are 21 mW and 15 mW, respectively. A source node is randomly selected among the sensor nodes and transmits data packets of size 128 bytes to a mobile sink group. The mobile sink group consists of 10 member sinks with an average speed of 10 m/s, and the group radius is set to 100 m. The Reference Point Group Mobility Model [38] is used to simulate group mobility.

We evaluate performance using two metrics: energy consumption and data delivery ratio. Energy consumption is defined as the total communication energy consumed for transmitting and receiving data packets in the network. The data delivery ratio is defined as the ratio of the number of data packets successfully received by mobile sinks to the total number of generated data packets. Each simulation is repeated 10 times with different network topologies, and the results are averaged.

Figure 3a illustrates an example of data dissemination based on a selected subgroup configuration. Figure 3b presents the cost values for all possible subgroup combinations. The total number of evaluated subgroup combinations is 1023, corresponding to all possible non-empty subsets of a 10-member sink group. The minimum cost is observed at the 726th evaluated configuration, indicating the optimal subgroup selection.

Figure 3c shows the results of cost evaluation repeated 100 times with randomly distributed member sinks to assess the robustness of the proposed model. The results exhibit low variance across trials, demonstrating the stability of the proposed cost model.

On average, the proposed approach reduces energy consumption by approximately 24% compared to the unicasting-based method and 44.5% compared to the flooding-based method.

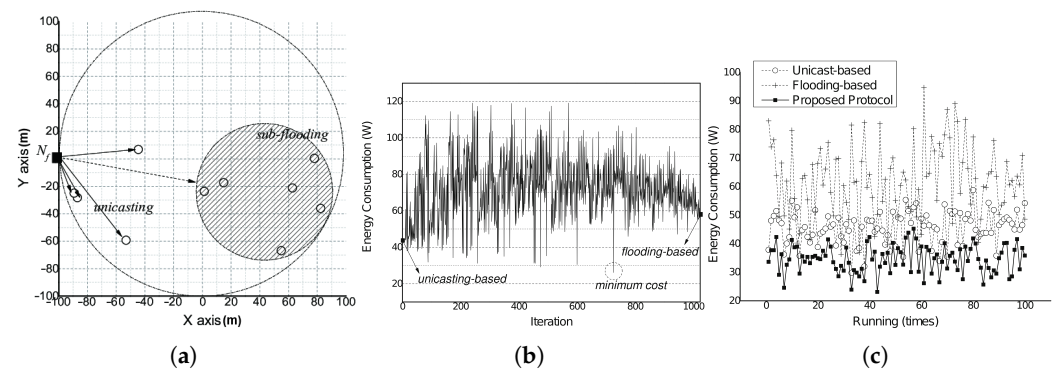


Figure 3. (a) An example of data dissemination based on a selected subgroup configuration within a mobile sink group; (b) cost values for all possible subgroup combinations; (c) results of cost evaluation repeated over 100 trials to assess the robustness and stability of the proposed cost model.

4.2. Simulation Results

Figure 4a shows the energy consumption as a function of the number of sensor nodes. As the number of sensor nodes increases, M-Geocasting incurs significantly higher energy consumption compared to other protocols since more sensor nodes participate in flooding-based data dissemination, resulting in increased transmission overhead.

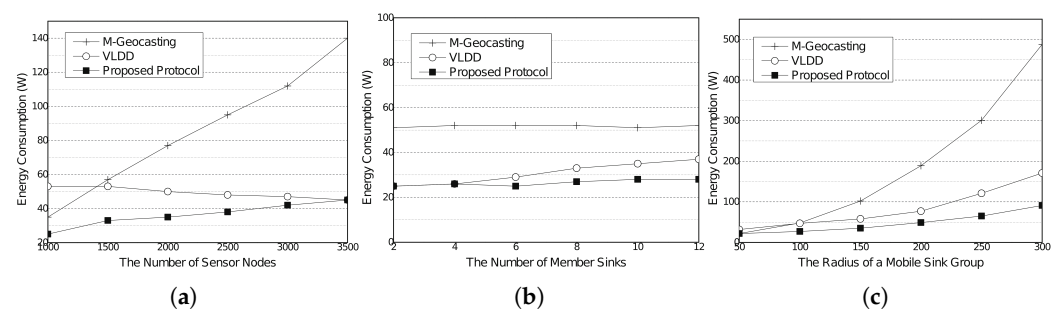


Figure 4. (a) Energy consumption versus the number of sensor nodes; (b) energy consumption versus the number of member sinks; (c) energy consumption versus the radius of a mobile sink group.

VLDD exhibits higher energy consumption than M-Geocasting in low-density scenarios due to inefficient routing paths. However, its energy consumption decreases slightly as node density increases, because more efficient routing paths with fewer hops can be selected.

The proposed protocol adapts to varying node densities by selecting an appropriate combination of flooding and unicast. As a result, it achieves energy consumption comparable to M-Geocasting in low-density scenarios and to VLDD in high-density scenarios while consistently maintaining lower or comparable energy consumption across all cases. These results are consistent with the analytical observations presented in Section 4.1.

Figure 4b shows the energy consumption as a function of the number of sinks in a mobile sink group. M-Geocasting maintains nearly constant energy consumption regardless of the number of sinks, due to the inherent nature of flooding-based dissemination, where all nodes within the region participate in data forwarding.

In contrast, VLDD exhibits increasing energy consumption as the number of sinks grows, since additional routing paths are required to deliver data to each individual sink.

The proposed protocol achieves consistently lower energy consumption by selectively applying flooding only to densely located sinks and unicasting to sparsely located sinks. This selective data dissemination effectively eliminates unnecessary flooding regions and reduces redundant transmissions. These results are also consistent with the analytical findings in Section 4.1.

Figure 4c shows the energy consumption as a function of the group radius. As the group radius increases, M-Geocasting exhibits a rapid (near-exponential) increase in energy consumption, because the flooding region expands, involving a larger number of sensor nodes.

VLDD shows approximately linear growth in energy consumption, as the data dissemination paths become longer with increasing group radius. However, VLDD does not account for the spatial clustering of sinks. Consequently, when sinks are closely located, identical data packets are repeatedly transmitted over the same multi-hop routing paths. This severe redundancy not only wastes transmission energy but also significantly increases the probability of MAC-layer collisions and channel contention. The proposed protocol completely bypasses this bottleneck by effectively grouping nearby sinks into a flooding subgroup, thereby reducing redundant unicasting transmissions. Consequently, it achieves lower energy consumption across varying group sizes. These observations further validate the effectiveness of the proposed hybrid data dissemination strategy.

To rigorously evaluate the reliability of the routing protocols, we employ the average data delivery ratio as a primary performance metric. The average data delivery ratio is defined as the ratio of the total number of successfully delivered data packets received by all member sinks to the total number of data packets originally generated and transmitted by the source node. In our quantitative evaluations, this metric is normalized and expressed as a decimal value bounded between 0.0 and 1.0, where 1.0 explicitly denotes a perfect 100% packet delivery success rate.

Figure 5a shows the average data delivery ratio as a function of the number of sensor nodes. M-Geocasting, which relies on flooding, exhibits a low delivery ratio in sparse networks due to limited connectivity. However, its performance improves significantly as the network becomes denser since more forwarding paths become available.

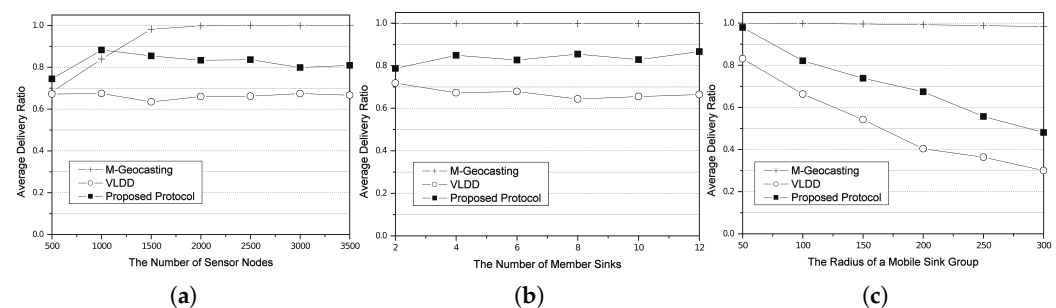


Figure 5. (a) Average data delivery ratio versus the number of sensor nodes; (b) average data delivery ratio versus the number of member sinks; (c) average data delivery ratio versus the radius of a mobile sink group.

In contrast, VLDD shows a relatively lower delivery ratio compared to the other protocols and is less sensitive to node density. This behavior is mainly due to its reliance on multi-hop unicasting, where packet delivery is affected by cumulative transmission failures over multiple hops. The proposed protocol achieves a delivery ratio higher than VLDD but slightly lower than M-Geocasting due to its hybrid nature. As the proportion of sinks served by flooding increases, the overall delivery ratio improves. These results are consistent with the trade-off between reliability and energy efficiency observed in Section 4.1.

Figure 5b shows the average data delivery ratio as a function of the number of member sinks. M-Geocasting maintains a consistently high delivery ratio regardless of the number of sinks due to its flooding-based data dissemination.

VLDD shows decreasing delivery performance as the number of sinks increases, since additional sinks require longer and more complex routing paths, increasing the likelihood

of transmission failures. In contrast, the proposed protocol improves its delivery ratio as the number of sinks increases, because a higher number of sinks increases the probability of spatial clustering. This allows the proposed protocol to exploit partial flooding for nearby sinks, thereby improving delivery reliability.

Figure 5c shows the average data delivery ratio as a function of the group radius. In this scenario, the number of sensor nodes and member sinks remains fixed. M-Geocasting maintains a high delivery ratio regardless of the group size due to the robustness of flooding, although this comes at the cost of significantly higher energy consumption, as observed in Section 4.1.

Both VLDD and the proposed protocol exhibit decreasing delivery ratios as the group radius increases. This is because larger group sizes increase the average distance between the source and sinks, resulting in longer multi-hop paths and higher packet loss due to fading, interference, and cumulative transmission errors.

In the proposed protocol, as the group becomes larger and more sparsely distributed, a greater proportion of sinks are served through unicasting rather than flooding. This increases the impact of multi-hop transmission failures, leading to a reduction in delivery ratio. Despite this limitation, the proposed protocol still outperforms VLDD due to its ability to exploit localized flooding for clustered sinks.

Overall, these results highlight the inherent trade-off between energy efficiency and delivery reliability. While flooding-based approaches achieve higher delivery ratios, they incur excessive energy consumption, whereas unicasting-based methods are more energy-efficient but suffer from lower delivery reliability. The proposed protocol effectively balances this trade-off.

To provide an intuitive comparison of the overall performance, Table 4 consolidates the average improvement ratios of the proposed protocol against the baseline protocols across all evaluated scenarios.

Table 4. Summary of average performance improvements in the proposed protocol.

Performance Metric	Compared Protocol	Average Improvement/Observation
Energy Consumption	vs. VLDD	~24.0% reduction
Energy Consumption	vs. M-Geocasting	~44.5% reduction
Data Delivery Ratio	vs. VLDD	Improved reliability
Data Delivery Ratio	vs. M-Geocasting	Slight reduction (trade-off for energy savings)

4.3. Discussion and Limitations

While the proposed hybrid mobile groupcasting protocol significantly improves energy efficiency under heterogeneous spatial distributions, there are certain limitations and operational edge cases to consider in practical deployments.

- **Non-uniform Node Distribution and Extreme Sparsity:** The proposed protocol relies on geographic routing (e.g., GPSR) to forward packets toward the group area. In disaster response or battlefield environments where sensor nodes are distributed non-uniformly or extremely sparsely, geographic routing frequently encounters routing voids. This forces the protocol into perimeter routing mode, which inevitably increases transmission delay and energy overhead.
- **High Mobility Speeds:** If the mobile sink group moves at excessively high speeds, the location updates sent to the data source may experience propagation delays. Consequently, the source might compute subgrouping based on outdated current area (CA) information, causing data packets to be forwarded to a location the group has already left, thereby degrading the data delivery ratio.

- **Multiple Disconnected Dense Regions:** To strictly minimize computational overhead at the source and intermediate nodes, the current heuristic restricts the partition to a single flooding subgroup and a unicasting subgroup. If a sink group splits into multiple disconnected dense regions, a single flooding subgroup strategy may either cover large empty spaces (causing energy waste) or force the protocol to rely heavily on unicasting. Exploring multi-flooding subgroup optimizations remains a future challenge.
- **Update Frequency and System Oscillation:** The protocol's efficiency depends on the timely updating of subgroup configurations. Excessively high update frequencies generate significant control overhead, while low frequencies lead to suboptimal routing. Furthermore, if sinks continuously move in and out of the dense region at boundaries, it may cause system oscillation between flooding and unicasting modes.

These limitations highlight the need for further optimizations, such as integrating predictive mobility models and adaptive parameter tuning, which we defer to future work.

5. Conclusions

In this paper, we proposed an energy-efficient, strictly lightweight hybrid mobile groupcasting protocol tailored for spatially heterogeneous mobile sink groups in wireless sensor networks. Driven by the core architectural philosophy of source-delegated computation, the protocol formulates the partition of highly dynamic sink groups into a single flooding subgroup and a unicasting subgroup as an analytical cost minimization problem executed entirely at the data source. Operating under a practical heuristic with a linear time complexity of $\mathcal{O}(|M|)$, the proposed framework completely relieves resource-constrained intermediate sensor nodes from dynamic in-network clustering or overhead-heavy state maintenance. Extensive evaluations via the QualNet 4.0 simulator verified the high effectiveness of this hybrid approach, demonstrating significant communication energy reductions of up to 24% and 44.5% compared to conventional unicasting-based and flooding-based protocols, respectively, while consistently maintaining high delivery resilience under cross-layer interference and wireless channel contention.

Despite these technological advancements, certain structural shortcomings and inadequacies remain to be addressed in future research. The current optimization framework relies on simplified network-layer cost models and idealized assumptions of uniform node placement, which may introduce sub-optimal performance bounds in real-world deployments featuring non-uniform node densities or extreme geographical sparsity where perimeter routing voids occur. Furthermore, our simplified single-flooding subgroup heuristic risks over-allocating communication resources if the mobile group fragments into multiple detached high-density clusters, while high sink velocities may trigger location-update propagation delays and mode oscillation at boundary zones. To bypass these limitations, our future research will focus on expanding the mathematical model to support multi-subgrouping partitioning optimizations, integrating lightweight machine learning algorithms for predictive trajectory and mobility modeling, and adapting the hybrid data dissemination framework to highly dynamic 3D environments such as unmanned aerial vehicle (UAV)-assisted networks.

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