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Abstract: Wireless Sensor Networks (WSNs) are key enablers of efficient communication in the Internet of Things (IoT) ecosystem. These networks comprise numerous sensor nodes that collaboratively collect and transmit data, requiring adaptive and energy-efficient management. However, high node density and resource limitations introduce challenges such as control overhead, packet collisions, interference, and energy inefficiency. To mitigate these issues, this paper adopts the Hybrid Wireless Mesh Protocol (HWMP), standardized under IEEE 802.11s for Wireless Mesh Networks (WMNs), as the routing protocol in WSNs. HWMP's hybrid design combining reactive and proactive routing is well-suited for dynamic and mobile environments, making it applicable to WSNs operating under similar conditions. Building on this foundation, we propose a community-aware topology control mechanism that constructs a Connected Dominating Set (CDS) to serve as the network's energy-efficient backbone. Node selection is guided by centrality metrics and detected community structures to enhance routing efficiency and network longevity. The mechanism is evaluated across six mobility scenarios characterized by realistic movement patterns. Comparative results show that incorporating community structure significantly improves routing performance and reduces energy consumption, validating the approach's effectiveness in real-world WSN deployments.

Keywords: topology control, centrality metrics, connected dominating set, energy-efficient, mobility models

1. Introduction

Wireless Sensor Networks (WSNs) have become essential in today's digital landscape, driven by the rapid expansion of the Internet of Things (IoT). By 2024, the global IoT ecosystem comprises more than 15 billion interconnected devices, with projections indicating this number will double by 2030 [1]. Notably, Greater China alone accounts for approximately 5 billion IoT devices, emphasizing the widespread adoption of this technology. Furthermore, about two-thirds of these devices actively utilize IoT capabilities, showcasing its deep integration into daily life. Among the numerous applications, remote asset monitoring is one of the most prevalent, solidifying WSNs as a critical enabler in the IoT paradigm.

Efficient management of WSNs is crucial for their optimal performance. Modern networks must exhibit self-organization and autonomous maintenance [2]. The most common scenario involves networks formed mainly by mobile sensor nodes deployed in diverse environments. With technological advancements, WSNs are evolving into comprehensive sensing systems within the IoT framework, facilitating various applications such as environmental monitoring, healthcare, and smart cities [3]. As a result, mobile sensor nodes are becoming a significant research focus, aiming to leverage real-time information for enhanced personal and environmental benefits.

In WSNs, sensor nodes act as data collectors and relays [2]. However, due to the large number of nodes present in these networks, it is neither practical nor energy-efficient for all nodes to participate in

routing. Common challenges include routing overhead, high packet collision probability, interference, and energy inefficiency.

To address these challenges, it becomes necessary to implement robust and scalable routing strategies that ensure energy-efficient communication. In this work, we adopt the Hybrid Wireless Mesh Protocol (HWMP) initially designed for Wireless Mesh Networks (WMNs) and standardized in IEEE 802.11s as the routing protocol within a WSN context [4,5]. Despite its origins in WMNs, HWMP's hybrid design combines proactive and reactive routing modes, making it well-suited for dynamic and decentralized environments such as mobile WSNs [6]. This methodological alignment allows us to treat the WSN as a mesh-based system for this study, leveraging WMN features while addressing the resource and energy constraints inherent to WSN deployments.

Furthermore, mobile sensor networks often follow human mobility patterns. Traditionally, researchers relied on random mobility models such as the Random Waypoint Mobility (RWM) model [7], favored for its simplicity. However, these models fail to accurately represent real-world mobility patterns. Subsequent research has highlighted the importance of three key mobility properties: spatial, temporal, and social. Among these, social properties are particularly relevant, as they define connectivity characteristics between different nodes. Consequently, more realistic mobility models have emerged, including SWIM [8], SLAW [9], SMOOTH [10], and disaster area models [11].

Networks with human-like mobility patterns often exhibit an organized community structure. A community is defined as a subset of nodes within a network where intra-community connections are denser than those with the rest of the network [12]. Various community detection algorithms have been developed, including heuristic-based [13–15], balanced color heuristics [16], and optimization-based approaches [17–19]. Additionally, centrality-based methods, such as those in [20,21], leverage centrality metrics like betweenness centrality to identify community boundaries. These techniques are comprehensively reviewed in [22–24].

Integrating numerous smart devices with social relationships justifies the incorporation of social characteristics into network design strategies [25,26]. Given the challenges in WSNs and their overlap with WMNs in mesh-based topologies, implementing topology control mechanisms that consider nodes' social interactions is essential for improving network efficiency and energy conservation.

In summary, this paper proposes and evaluates a community-aware topology control mechanism based on the centrality characteristics of a WSN. First, various mobility models are analyzed and applied to sensor nodes. Once the nodes exhibit mobility, a topology control mechanism is designed, leveraging centrality metrics and community detection techniques. The final objective is constructing a Connected Dominating Set (CDS) that forms an energy-efficient routing backbone. The proposed approach's performance is compared with an unstructured network and a topology control mechanism that disregards community structure across multiple scenarios.

The remainder of this paper is structured as follows. Section 2 presents a theoretical framework to understand the study better. Section 3 reviews related works. The design and evaluation of the proposed topology control mechanism are detailed in Section 4. Section 5 presents results and discusses. Finally, Sections 6 outline the conclusions and future research directions.

2. Theoretical Background

This section presents the foundational elements that support our proposed topology control mechanism. Although the study focuses on a Wireless Sensor Network (WSN) scenario, we adopt the Hybrid Wireless Mesh Protocol (HWMP) initially defined in the IEEE 802.11s standard for Wireless Mesh Networks (WMNs) as the routing protocol [5]. HWMP's hybrid nature, combining proactive and reactive strategies, makes it highly adaptable to dynamic, mobile, and decentralized WSN environments [6]. By incorporating this protocol, we enable mesh-like routing behavior within WSNs, aligning with our goal of achieving scalable and energy-efficient topologies.

To build a robust theoretical foundation, we next examine the key components of the system: WSN characteristics and the rationale for using HWMP, followed by topology control strategies, human

mobility models, community detection methods, and centrality metrics. These concepts provide the necessary background to understand the design and evaluation of our community-aware topology control mechanism.

2.1. Wireless Sensor Networks

Wireless Sensor Network (WSN) comprises spatially distributed sensor nodes that monitor and record environmental conditions such as temperature, sound, and pressure, transmitting the collected data to a central location for analysis and processing. Each sensor node typically consists of a microcontroller, a radio transceiver with an internal or external antenna, an electronic circuit for interfacing with the sensors, and an energy source, usually a battery [27,28]. These nodes collaborate to form a network capable of self-organization and self-healing, making WSNs suitable for environmental monitoring, industrial process control, and healthcare applications [29–31].

Maintaining reliable communication becomes challenging when sensor nodes are mobile or deployed over extensive areas. To address this, integrating concepts from Wireless Mesh Networks (WMNs) into WSNs has proven effective [32]. WMNs are low-cost, self-configurable multi-hop networks designed to provide ubiquitous wireless connectivity through mesh routers (MRs) [33]. These MRs are typically powerful devices with multiple radio interfaces that create a robust backbone, facilitating connectivity among nodes [34].

By incorporating mesh routers into WSNs, the network benefits from enhanced scalability, extended coverage, and improved fault tolerance. This mesh routers can handle high traffic loads and manage dynamic topologies, addressing common challenges in WSNs, such as limited energy resources and communication range. This integration enables the development of more resilient and efficient sensor networks that are capable of supporting various applications in complex environments [32,35].

2.2. Hybrid Wireless Mesh Protocol

The Hybrid Wireless Mesh Protocol (HWMP), initially specified in the IEEE 802.11s standard, is pivotal in enabling dynamic and energy-efficient routing in wireless mesh-based architectures [36]. While HWMP was initially designed for Wireless Mesh Networks (WMNs), its flexible hybrid routing strategy combining both reactive and proactive mechanisms makes it highly applicable to Wireless Sensor Networks (WSNs), particularly in Internet of Things (IoT) scenarios where mobility and topology changes are frequent.

HWMP's hybrid approach supports efficient data dissemination under varying network conditions. In its reactive mode, route discovery is initiated only when a source station (STA) needs to transmit data to an unknown destination. This is achieved by broadcasting a Path Request (PREQ) message, which allows intermediate nodes to establish or update paths to the target node [4,37]. This on-demand mechanism is particularly beneficial for energy-constrained WSNs with low node density and dynamic traffic patterns, as it minimizes unnecessary control overhead.

On the other hand, the proactive mode of HWMP configures one or more nodes as root stations that periodically broadcast PREQ messages to maintain updated routing information. Nodes receiving these messages calculate optimal paths to the root, considering metrics such as link quality and hop count [37]. This mode is advantageous in more stable topologies and supports hierarchical communication flows, which can contribute to reducing energy consumption through structured routing.

Moreover, HWMP introduces a hierarchical network organization by categorizing nodes into specific roles, such as mesh routers, bridge routers, and end stations [38]. This role-based structure enhances scalability and energy efficiency by delegating communication tasks according to each node's capabilities and positions within the network.

By integrating HWMP within WSNs, this work leverages mesh-like communication patterns to build scalable, robust, and energy-aware routing topologies, aligning with the broader goals of efficient IoT connectivity and long-term network sustainability [32].

2.3. Topology Control

Topology control is a foundational technique in the domain of wireless networks. It facilitates the modification of network parameters, thereby enabling the creation and maintenance of a particular network topology, thus achieving predetermined network properties [39]. Its significance is particularly pronounced in the domains of ad hoc networks and Wireless Sensor Networks (WSNs), where it plays a pivotal role. The fundamental objective of topology control is to reduce energy consumption while mitigating radio interference. Consequently, it serves to minimize packet collisions [40].

One of the primary concerns within client WMNs is the establishment of an appropriate network topology that serves as the foundation for the implementation of higher-level routing protocols [41]. Given the inherent dynamism of these networks, where topologies are in continuous change, routing schemes must demonstrate robustness in the face of these alterations.

A predominant approach to topology control mechanisms revolves around the adjustment of node transmission power [40,42,43]. In such systems, the employment of high transmission power levels can lead to complications related to interference, while low power levels result in network fragmentation. Alternatively, certain mechanisms are contingent upon the power mode of individual nodes, encompassing transmission, reception, idle, and sleep states. Furthermore, certain mechanisms adopt a clustering approach, often relying on the strategic selection of a Connected Dominating Set (CDS), as exemplified in the works of Qi et al. [44] and Farooq et al. [45].

The challenge inherent in finding a Dominant Set (DS) hinges on identifying a subset D of nodes in the network graph, such that each node belongs to D or is adjacent to it [46]. The formation of a connected graph by the nodes within this DS results in the transition of the DS to the form of a CDS. The nodes that comprise the CDS constitute the network's backbone. The quality of the resultant reduced topology can be assessed on various criteria, including connectivity, energy efficiency, throughput, and resilience to mobility dynamics [47].

2.4. Human Mobility Models

In the domain of Wireless Sensor Networks (WSNs) and Wireless Mesh Networks (WMNs) simulations with mobility devices, the employment of representative scenarios that closely resemble real-world conditions is of critical importance. The attainment of this degree of realism frequently necessitates the incorporation of mobility traces into the networks under examination [48]. However, acquiring authentic mobility traces for particular scenarios poses a considerable challenge, necessitating significant time, resources, and the deployment of numerous devices. Consequently, a pragmatic approach entails the utilization of synthetic traces generated by mobility models. These models encapsulate human behavior patterns through mathematical formulations, thereby offering a means to approximate the movements of network nodes. Leveraging mobility models enables the production of network performance evaluations that closely mirror real-world outcomes.

In this context, the Random Waypoint Mobility (RWM) [7] model is one of the most frequently utilized mobility models. In this study, we have considered the most relevant models in light of contemporary human behavior. Table 1 summarizes the main characteristics of the discussed models relevant to simulations in WSN and WMN. This comparison emphasizes the complexity, realism, and application contexts of each model, which supports selecting appropriate models for specific simulation requirements.

Table 1. Comparison of human mobility models relevant to WSN/WMN simulations.

Mobility Model	Complexity	Realism Level	Key Features	Application Scenarios
Lévy Walk / TLW [49]	Low	Moderate	Power-law distributed movement steps; truncated variation simulates purposeful walks	Wildlife modeling, general-purpose random mobility
SWIM [8]	Low	High	Proximity to home and popular spots; cell-based simulation	Urban mobility, social interaction modeling
SLAW [9]	High	Very High	Self-similarity; mobility zones; fractal waypoints	Campus, malls, theme parks, routine/irregular users
SMOOTH [10]	Medium	High	Popularity-based clusters; simplified SLAW behavior	Office environments, clustered mobility
Disaster Area Model [11]	Medium	High	Role-specific movements; simulated emergency zones	Emergency response, disaster simulations
Map-Based SLAW [50]	High	Very High	Geographical constraints; building-aware navigation	Realistic urban topologies, signal propagation studies

2.4.1. Lévy Walk Model

In the study of mobility models, the Lévy walk model is a notable paradigm. This model encapsulates aspects of human behavior by integrating statistical characteristics associated with Lévy walk movements, a form of random motion primarily governed by diffusion processes [51]. Initially devised to elucidate the behaviors of certain animal species [52,53], the Lévy walk model transformed when Rhee et al. introduced the concept of a truncated Lévy walk (TLW) model [49]. The TLW model attempts to replicate human decision-making processes when navigating toward intended destinations, lending a degree of intentionality to the otherwise stochastic nature of Lévy walks.

The TLW model has notably served as the basis for subsequent mobility models, including SWIM, SLAW, and SMOOTH. These models have contributed to a more nuanced understanding of network node mobility patterns within the context of WSNs.

2.4.2. Small World in Motion (SWIM)

Small World In Motion (SWIM) is an efficient, parameter-sparse mobility model designed to emulate human mobility patterns. Unlike other models, which require many input parameters, SWIM captures human behavior by simulating tendencies, such as frequenting nearby places or popular social spots, over time.

SWIM divides the simulation area into cells equivalent in size to the node's transmission radius. Nodes have individual weights based on cell popularity and distance from their randomly assigned home location. SWIM also uses a cell distance weight parameter (α), which governs node behavior; higher values promote proximity to home and neighbors, while lower values encourage exploration of popular locations. SWIM offers a streamlined approach to modeling complex social mobility patterns in wireless networks [8].

2.4.3. Self-Similar Least-Action Human Walk (SLAW)

Self-Similar Least-Action Human Walk (SLAW) is a comprehensive mobility model designed to simulate complex human behaviors. While it involves more input parameters than SWIM, SLAW leverages contemporary statistical patterns derived from human mobility studies, including truncated power-law distributions, pause times, inter-contact times, fractal waypoints, and individually defined mobility zones [9,54,55].

SLAW is designed to represent diverse social scenarios, such as university campuses, shopping centers, restaurants, and theme parks. It can generate mobility traces for regular trips, which are common for individuals with set routines, as well as sporadic trips, which are ideal for modeling those who visit random locations. This flexibility distinguishes SLAW from models such as RWM or TLW.

2.4.4. SMOOTH Mobility Model

SMOOTH emerges as a pragmatic and realistic mobility model, offering a simplified alternative to SLAW while retaining essential human behavioral characteristics [10]. Like SLAW, SMOOTH incorporates critical mobility and human behavior attributes.

Although the Hurst parameter is simpler than that of SLAW, it still yields commendable performance. In SMOOTH, the movement of nodes is intricately linked to social behavioral patterns and community dynamics. For example, certain offices in a building, such as a conference room, may receive more frequent visits than others. Consequently, SMOOTH generates clusters of varying sizes and randomly distributes them. The number of clusters is an input parameter, and each group is assigned a different popularity value. Popularity dictates the frequency of visits to each group, thus influencing the likelihood that a group will be selected as a destination. This approach effectively captures the dynamics of human behavior within various settings [56].

2.4.5. Disaster Area Model

In an intriguing approach outlined in [11], a unique mobility model is introduced to simulate disaster scenarios. The primary objective is to create scenarios in which to test and assess the optimal and efficient performance of communication systems under challenging circumstances. Due to the critical importance of reliable communication systems in disaster scenarios, this model paves the way for evaluating topology control techniques in such environments. Consequently, it has garnered our attention and is under consideration for integration into this research effort.

The disaster area model is based on the concept of room separation, where care rooms and the locations of rescue personnel are strategically distributed throughout the simulation area. Key areas incorporated into the model include the incident location (IL), the emergency patient waiting area (PWT), the casualties clearing station (CCS), the transport zone (comprising the ambulance and helicopter areas), and the technical operation command (TOC) [11] .

2.4.6. Map-Based Mobility Model

Most mobility models, including SWIM, SLAW, and SMOOTH, operate without considering geographic boundaries. These models are scale-free by nature and show no variation in response to geographical constraints. However, the work presented by [50] is a notable departure from this convention. It incorporates geographical restrictions into the SLAW mobility model, producing the Map-Based Self-Similar Least-Action Human Walk (MSLAW) model. This enhancement introduces a novel dimension to performance results in mobile network simulations.

Furthermore, integrating geographic boundaries enables interaction with propagation models, leveraging the distribution of buildings and environmental obstructions to improve the model's accuracy in representing real-world scenarios.

2.5. Community Detection

In graph theory, it is important to understand the difference between network partitioning and community detection. Network partitioning involves dividing a network into groups of roughly equal size. The number of groups and their sizes are predetermined. However, communities in reality exhibit varying sizes. Community detection, on the other hand, seeks to uncover these network properties and accommodate the inherent heterogeneity found in actual communities.

Several metrics are used to evaluate the quality of a community structure, with modularity being the most widely embraced. Defined by Newman and Girvan [17], modularity quantifies the discrepancy between edge density within a community and the expected density if the edges were

distributed randomly in the network. For weighted networks, modularity (Q) is calculated using Equation 1.

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \tag{1}$$

where, A is the adjacency matrix, A_{ij} represents the edge weight between nodes i and j, k_i denotes the sum of edge weights connected to node i, c_i signifies the assigned community for node i, $\delta(u,v)$ equals 1 if $u = v$ and 0 otherwise, and m is half the sum of all edge weights in the graph.

Essentially, community detection involves grouping nodes based on strong internal connections and weaker external connections. Many algorithms have been proposed for this task, but optimal community detection algorithms are NP-hard, particularly those focused on maximizing modularity. Therefore, approximation algorithms are often preferred. Many existing algorithms focus on binary networks, where edges have a weight value of 1 if they exist and 0 if they do not, as in certain environments, such as biological networks. However, real-world networks are typically weighted, requiring community detection algorithms that account for these weight values [57].

2.6. Centrality Metrics

In the field of social network analysis, graph-theoretic metrics are widely used to identify the most critical nodes in a network. Centrality measures are particularly valuable because they are designed to identify the most influential actors. The following components are considered the most relevant for this study.

2.6.1. Betweenness Centrality

Betweenness centrality is assumed to play a central role in this study. It is defined as the fraction of all shortest paths between pairs of nodes that pass through a given node. In essence, this metric quantifies the extent to which a node can control the flow of information between other nodes within the network. The betweenness centrality C_B of a node v is shown in Equation 2.

$$C_B(v) = \sum_{j=1}^{N} \sum_{k=1}^{j-1} \frac{g_{jk}(v)}{g_{jk}} \tag{2}$$

where g_{jk} is the number of shortest paths between j and k, $g_{jk}(v)$ is the number of shortest paths between j and k that pass through v and N is the total number of nodes in the network [58].

Regarding communities, in [57] two centrality metrics derived from the betweenness centrality are defined: Intra-centrality and Inter-centrality.

2.6.2. Intra-Centrality

Intra-centrality ($intraC_B$) measures the influence of a node within its community. It is calculated by determining its betweenness centrality while considering only nodes that belong to the communication, as shown in Equation 3.

$$intraC_B(v) = \sum_{j=1}^{N(C_v)} \sum_{k=1}^{j-1} \frac{g_{jk}(v)}{g_{jk}}, \quad i,j \in C_v \tag{3}$$

where C_v is the community to which v belongs and $N(C_v)$ is the total number of nodes that belong to C_v. If a node belongs to more than one community, then it has an $intraC_B$ value for each community to which it belongs. This occurs in the case of overlapping communities.

2.6.3. Inter-Centrality

The inter-centrality ($interC_B$) of a node v for two communities C_m and C_n is defined as the betweenness centrality of v considering only the nodes that belong to either community (see Equation

4). If a node belongs to more than one community, then it has an intra-community betweenness centrality value for each community to which it belongs (in the case of overlapping communities). In general, inter-centrality measures the capability of a node to communicate these two communities. Each node has a $interC_B$ value for each pair of communities in the network.

$$interC_B(v) = \sum_{j=1}^{N(C_m \cup C_n)} \sum_{k=1}^{j-1} \frac{g_{jk}(v)}{g_{jk}}, \quad i,j \in C_m \cup C_n \tag{4}$$

Intra-centrality is a useful method for identifying the most influential nodes within a single area. However, inter-centrality does not appear to be a viable method for detecting nodes that bridge two or more densely populated regions. This is because advance knowledge of all the communities in the network is required, and each node would generate an $interC_B(v)$ value for each pair of communities, implying high memory usage.

2.6.4. Bridging Centrality

Bridging centrality is a derivative of betweenness centrality. It identifies nodes that facilitate substantial information flow between densely connected regions, which are often characterized by high modularity [59]. Bridging centrality (C_{Brid}) combines betweenness centrality (C_B) and the bridging coefficient (BC) of a node, as shown in Equation 5. BC is defined in Equation 6.

$$C_{Brid}(v) = BC(v) \times C_B(v) \tag{5}$$

$$BC(v) = \frac{d(v)^{-1}}{\sum_{i \in N(v)} \frac{1}{d(i)}} \tag{6}$$

where $d(v)$ is the degree of node v and $N(v)$ is the set of neighbor nodes of v. According to [59], the nodes that are actually considered bridging nodes are those within the 25% with the highest C_{Brid} values in the network.

3. Related Work

Due to their potential to improve network efficiency, topology control mechanisms for wireless sensor networks (WSNs) have garnered significant attention in the scientific community. This surge in interest has prompted numerous studies compiling various topology control techniques.

One of the primary objectives of topology control is to optimize energy usage and extend battery life. This challenge has spurred significant efforts within the scientific community to address this issue. For instance, in [39], a detailed overview of distributed topology control techniques is provided, with a primary emphasis on extending battery life in wireless sensor networks (WSNs). These techniques fall into two categories: 2D and 3D algorithms. 2D algorithms are further divided into power adjustment, power mode, clustering, and hybrid approaches. Conversely, 3D algorithms address topology control in specialized settings, such as indoor or underwater environments. Similarly, [60] presents a comprehensive review of topology control techniques in WSNs, with a focus on full coverage, barrier coverage, sweep coverage, energy management, and power control.

Furthermore, in [61], a taxonomy is introduced to classify topology control problems in WSNs. The two main classifications are network coverage and network connectivity. These works also emphasize the importance of energy management as a foundational framework for addressing topology control challenges. Similarly, Huang et al. [62] contribute to a taxonomy of topology control algorithms, primarily emphasizing energy efficiency for Internet of Things (IoT) applications. These algorithms fall into three categories: homogeneous, heterogeneous, and miscellaneous. The first two categories assume homogeneity or heterogeneity among network devices, respectively, while the "others" category considers factors such as device location, direction, and neighboring nodes.

In recent years, topology control based on discrete Markov processes has emerged as an effective strategy for extending the operational lifetime of star-configured wireless sensor networks (WSNs). This strategy models node state transitions in active, inactive, or sleep modes. It also dynamically optimizes duty cycles to minimize energy consumption without sacrificing connectivity [63,64]. Meanwhile, federated learning has gained prominence as a privacy-preserving approach to training AI models collaboratively across distributed devices, ranging from mobile phones to healthcare systems and autonomous vehicles, by keeping raw data localized and only exchanging model updates [65,66]. Comprehensive surveys of federated learning have identified several key challenges, such as non-independent and identically distributed data, data heterogeneity, communication efficiency, and model security. These surveys have also speculated about the potential evolution of federated learning toward artificial consciousness, which is subject to rigorous ethical scrutiny. Together, these studies outline the current state of the art at the intersection of energy-efficient WSN design and decentralized, privacy-aware machine learning.

Other studies focus on strategically placing network elements to improve topology. In [67], the authors review placement strategies, buffering capacity, and mobility models for implementing Throwboxes in delay-tolerant networks (DTNs). Throwboxes serve as relays between network nodes to improve delivery rates, reduce delays, and alleviate the load on mobile nodes.

Other studies emphasize devising adaptable topology control techniques. In [68], the focus is on topology control in mobile ad hoc networks (MANETs). The authors propose a method to determine the optimal topology during update intervals through node group prediction, thereby minimizing the nodes' cumulative energy consumption. Conversely, in [69], the authors specify topology control for monitoring landslides in WSNs. This flexible topology works in both normal and emergency conditions. This approach demonstrates the versatility and applicability of topology control in specialized contexts.

In the domain of community awareness, a considerable body of literature employs Social Network Analysis (SNA) methodologies, frequently utilizing centrality metrics such as betweenness centrality, degree centrality, and closeness centrality, among others. As demonstrated in [70], nodes with a high degree of centrality can influence the dependability of Wireless Mesh Networks (WMNs). The efficacy of the TDMA channel access scheduling algorithm implemented in high-centrality nodes is demonstrated through its implementation in the nodes, thereby showcasing network performance enhancements. In the study by Meghanathan et al. [71], centrality metrics are employed to identify Connected Dominating Sets (CDSs) in complex graphs. The formation of the smallest CDSs is often predicated on betweenness centrality. In addition, an investigation was conducted in [72] that entailed a comparison between degree, closeness, and betweenness centrality metrics to establish a WMN backbone. The findings indicated that betweenness centrality exhibited enhanced stability and fragmentation performance in networks with randomly distributed nodes. In contrast, Shifani et al. propose the IoT-based Secured Data Exchange Protocol (IoTSDEP) in order to further enhance community awareness through SNA in [73]. This paradigm enables social communities in Wireless Sensor Networks (WSNs) to share information in a decentralized and resilient manner. By leveraging lightweight encryption, secure routing, and intrusion detection, the system enhances efficiency, scalability, privacy, and trust.

A subset of research endeavors involves the integration of centrality metrics and community structures with the objective of enhancing network performance. As stated in the research paper "Bubble Rap" [74], a routing algorithm is provided that is rooted in social behavior. This algorithm integrates community structure knowledge and node centrality values to facilitate routing decisions. The "Bubble Rap" protocol is designed to facilitate the dissemination of data packets to prominent nodes within the network framework. This dissemination process is informed by a combination of global and local rankings, thereby ensuring the optimal delivery of information. In [57], an algorithm for packet forwarding is proposed in Delay-Tolerant Networks (DTNs), which utilizes community structures and metrics of intercentrality and intracentrality.

Despite the preponderance of prior studies in topology control that have focused on transmission power adjustment and node placement, there have been independent and joint endeavors to develop topology control and packet forwarding algorithms through the utilization of centrality metrics and community structures. This work introduces a community-aware topology control method for WSNs, emphasizing the discovery of a connected dominant set (CDS) within a homogeneous WMN. Nodes outside this CDS deactivate their routing functions, leading to reduced topologies. The proposed approach is evaluated and compared with a non community-aware topology control method exclusively reliant on centrality metrics.

4. Topology Control Mechanism

In this section, an overview of the environment under research is provided. In the following section, we delineate the community detection algorithm that was utilized for the evaluation. We proceed to assess various router selection methods based on centrality metrics and community structures. Consequently, an exhaustive evaluation of the resulting reduced topologies was conducted for all scenarios evaluated in this study.

4.1. Scenarios Under Consideration

In this study, the scenarios were selected according to the criteria outlined in [48] with the objective of closely replicating the environments of social behavior in real life. Each scenario under consideration comprises a WSN that has been expanded to a WMN, consisting of 100 nodes that adhere to the 802.11s standard. The nodes have been meticulously positioned within a delineated area measuring 1024 by 520 meters. In order to maintain uniformity and objectivity in the evaluation process, it is imperative that all simulations adhere to a consistent structural foundation. The duration of each simulation is fixed at 500 seconds. The distinguishing factor among these scenarios is the mobility model that governs the movement of the nodes. The integration of six distinct mobility models has been successfully executed. The following models are employed: The following terms are to be considered: SWIM, SLAW, SMOOTH, Disaster Area, Map-Based, and Random Waypoint.

The objective of this study is to validate performance enhancements across a spectrum of realistic settings. The input parameter configurations for the initial four mobility models comply with the specifications delineated in [8–11]. In the case of the map-based scenario, it emulates a portion of Cuenca, Ecuador. In the Random Waypoint Mobility (RWM) model, each node autonomously selects a destination and proceeds toward it along a straight path at a randomly determined speed within the range of v_{min} to v_{max}. For the purposes of this study, the node movement speed has been set to vary between 2 and 4 meters per second, with a maximum pause time of 20 seconds.

For all models of mobility, with the exception of the map-based model, the Bonnmotion software is employed [75]. Conversely, the map-based model utilizes SUMO software for emulation.

4.1.1. Community Detection

As previously indicated, the adoption of human mobility patterns by nodes within the network naturally gives rise to the formation of communities over time as a result of social interactions. These communities are distinguished by the observation of increased temporal and spatial interactions among their constituent nodes. Consequently, the initial step in devising a community-aware topology control mechanism is to identify and track these evolving communities within each scenario.

The Louvain algorithm, as delineated in [76,77], has been identified as the optimal approach for community detection. This algorithm is characterized by its global and centralized nature, with a foundation in modularity maximization. It demonstrates proficiency in the identification of communities within weighted networks. The acceleration of the Louvain algorithm is achieved through the implementation of the Grappolo tool, which utilizes parallel execution techniques as outlined in the work by Lu et al. [78].

The Louvain algorithm requires the weight matrix of the network's links as an input parameter. The construction of this matrix is predicated on the nodes and the connections between them. The

nodes are derived from the mobility traces of each mobility model, while the edge weights are determined by simulating the same nodes under the 802.11s standard and the HWMP protocol to establish connections [79].

That is, the edge weights are determined by the expression $max(c_a) - c_a$, where c_a represents the airtime link metric of 802.11s, and $max(c_a)$ denotes the maximum value of c_a observed throughout the network. The Airtime Link Metric is a quantitative metric that quantifies the channel resources required for transmitting a frame over a specific link. Lower metric values are indicative of more favorable links. Therefore, the maximum difference between the nodes' values, that is, $max(c_a) - c_a$, is indicative of the strength of the link between the two nodes. The output is a matrix comprising the nodes and the community to which each is assigned.

4.2. Routers Selection

In Section 2.6, the emphasis is placed on the significance of betweenness centrality and its derivatives in the context of network information flow regulation and forwarding. A higher betweenness centrality value for a node is indicative of greater control over the information flowing between nodes. Given that the topology under study exhibits a community structure due to the various applied mobility models, it becomes evident that topology control design should consider these communities. In accordance with the findings of prior studies [48,59,72], the decision has been made to utilize betweenness and bridging centrality metrics in the selection of routers.

This work proposes a methodology for selecting the most central nodes within each community based on betweenness centrality, as well as the nodes that optimally connect the communities to each other using bridging centrality. This approach is intended to establish a group of mesh routers (MRs) and thereby construct the backbone network.

For the bridging nodes, the selection criterion invariably encompasses the top 25% of nodes that exhibit the highest values of bridging centrality within the network. This percentage aligns with the conclusions drawn from prior research, as outlined in [59], where the definition of bridging nodes was derived from empirical studies.

In this study, we propose and assess three distinct selection methods for central nodes based on betweenness centrality within each community. The selection methods include the k most central nodes, Community-Aware Highest Betweenness Intra-Centrality Neighbor (C-A H$IntraC_B$N), and Community-Aware Highest Betweenness Centrality Neighbor (C-A HC_BN). Furthermore, a comparative analysis is incorporated with the topology control method proposed in [72], referred to as "2 Highest Betweenness Centrality Neighbors" (2HC_BN). The subsequent sections will provide a detailed exposition of each of these methods.

4.2.1. k-Most Central Nodes in Each Community

In this method, a specific number, denoted k, of the most central nodes within each community is selected based on their betweenness centrality (C_B) values. In this study, we specifically assess two values of k, namely $k = 1$ and $k = 2$. Furthermore, as previously mentioned, we identify the top 25% bridging nodes as MRs. These selected nodes will serve as MRs and form the backbone.

4.2.2. Community-Aware Highest Intra-Centrality Neighbor (C-A H$IntraC_B$N)

The proposed method entails the selection of a neighbor node with the highest $intraC_B$ value by each node in the network, thereby designating it as a router. In addition to the previously described methodology of selecting the top 25% of bridging nodes, the following steps are to be taken. As delineated in Equation 1, $intraC_B$ signifies the betweenness centrality of a node, evaluated exclusively within its community. Nodes that do not belong to the same community are assigned an $intraC_B$ value of 0 and therefore not considered for router selection. The approach of nodes selecting immediate neighbors as routers ensures that there are no isolated nodes left in the network, except for those without established peer links.

4.2.3. Community-Aware Highest Betweenness Centrality Neighbor (C-A HC_BN)

In this method, each node calculates its betweenness centrality (C_B) without taking into account the community of the node or the communities to which other nodes belong. Subsequently, each node selects its neighbor with the highest betweenness centrality value within the same community. In order to be considered eligible, neighboring nodes must belong to the same community as the node in question. Consequently, the node is only required to ascertain its community in order to restrict the selection to eligible neighbors.

4.2.4. 2 Highest Betweenness Centrality Neighbors ($2HC_BN$)

This mechanism is predicated exclusively on centrality metrics, eschewing any consideration of edge weights. In the $2HC_BN$ method, each node selects its two neighbors with the highest betweenness centrality values as mesh routers (MRs). As in C-A HC_BN, $2HC_BN$ is predicated on a CDS whose elements constitute the network backbone. This method does not take into account the community structure of the network. This decentralized approach enhances network performance and promotes greater energy efficiency in comparison to WMNs that lack topology control [72].

4.3. Network Connectivity Assessment

As previously employed in a related study [72], the efficacy of each method was assessed by evaluating two vital attributes of the resulting topologies: the fragmentation of the resulting backbone and the number of isolated nodes.

The quantification of graph fragmentation is achieved through the implementation of a metric delineated in [80] which conceptualizes fragmentation as the proportion of nodes that are disconnected from one another. It is asserted that the generated backbone should demonstrate an absence of fragmentation, thereby signifying that all selected router nodes must ensure the maintenance of direct or indirect connectivity. The presence of fragmentation in a network is indicative of its disconnection. However, while a connected backbone is vital, it does not necessarily ensure the absence of isolated nodes. To address this concern, a further evaluation of the number of isolated nodes associated with each proposed method is warranted. The utilization of these two evaluation measures in conjunction facilitates the selection of the optimal method concerning network connectivity.

As illustrated in Figures 1, 2, and 3, the topologies generated by each proposed method are depicted, with the corresponding backbones shown in each case. In the accompanying illustrations, blue nodes are indicative of selected routers (MRs), green nodes are representative of mesh client nodes (MCs) that do not route traffic, and red nodes are representative of isolated nodes. The ensuing results are contingent upon the SWIM scenario, with a temporal frame of 30 seconds. However, an exhaustive analysis of snapshots from all six proposed scenarios reveals consistent patterns.

The results obtained from each method are summarized in Table 2. This table includes the backbone fragmentation and the count of isolated nodes. The method of selecting k most central nodes in each community, with $k = 1$ and $k = 2$, reveals the presence of fragmented backbones and numerous isolated nodes (see Figure 1). This observation indicates that the selection of routers is not optimal. Conversely, the C-A H*IntraC*N method achieves complete backbone connectivity without isolated nodes, selecting 49% nodes as mesh routers (see Figure 2). In a similar vein, the methods C-A HC_BN and $2HC_BN$ both attain full backbone connectivity, with 40% and 47% of the nodes selected as routers, respectively (see Figure 3). In summary, the C-A HC_BN and $2HC_BN$ methods have been shown to consistently yield superior network connectivity results. For this reason, they have been selected for further analysis in this study.
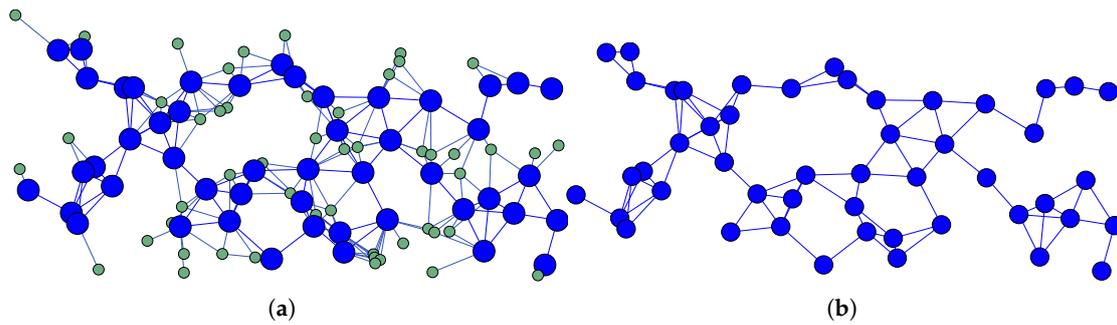
Figure 2. Reduced Topology and Backbone generated with C-A H$IntraC_B$N method selecting 25% most bridging nodes in SWIM model at $t = 30$ sec. (**a**) Reduced Topology. (**b**) Backbone.
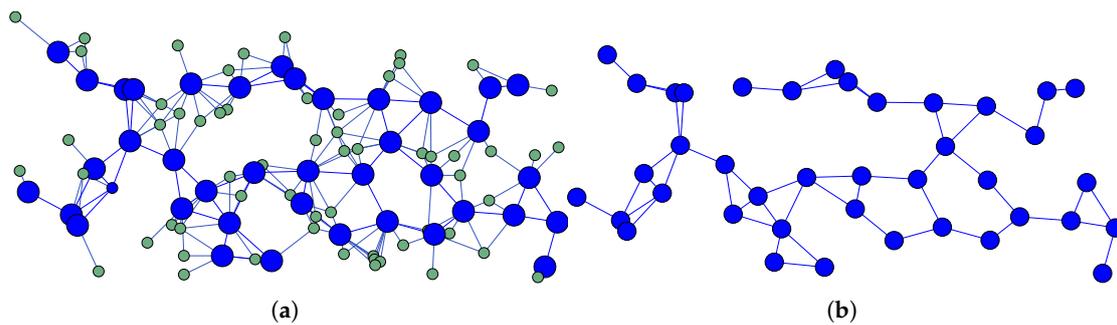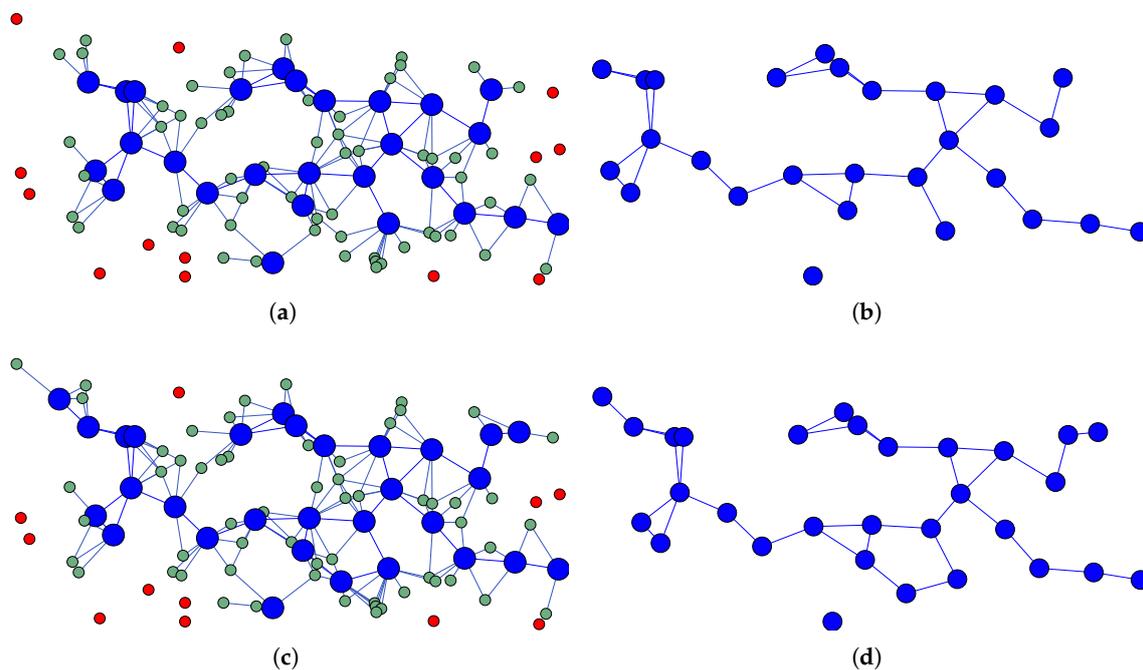

Figure 3. Reduced Topology and Backbone generated with C-A HC_BN method selecting 25% most bridging nodes in SWIM model at $t = 30$ sec. (**a**) Reduced Topology. (**b**) Backbone.

Figure 1. Reduced Topology and Backbone generated with k most central nodes in each community method selecting 25% most bridging nodes in SWIM model at $t = 30$ sec. (**a**) Reduced Topology with $k = 1$. (**b**) Backbone with $k = 1$. (**c**) Reduced Topology with $k = 2$. (**d**) Backbone with $k = 2$.

Table 2. Results of network connectivity achieved for every proposed method in the SWIM scenario at $t = 30$ seg.

Method	Backbone fragmentation	Isolated nodes	Routers selected
$k = 1$ most central nodes in each community	0.0741	13	27%
$k = 2$ most central nodes in each community	0.0667	11	30%
C-A H$IntraC_BN$	0	0	49%
C-A HC_BN	0	0	40%
2HC_BN	0	0	47%

4.4. Analysis of the Resulting Topologies

In this section, an analysis of the resulting topologies obtained through the C-A H C_BN control mechanism is carried out. To conduct the analysis, 50 simulations were executed, with each simulation lasting 500 seconds. Additionally, topology control was updated at an interval of 5 seconds for each mobility model, which comprised 100 mesh nodes.

The initial segment of Table 3 presents the outcomes of the number of routers selected by the C-A H C_BN method for the six mobility models. The results are expressed in terms of minimum, maximum, mean, and standard deviation values, denoted by σ. On average, approximately 39% of the nodes function as routers in all scenarios. The RWM scenario necessitates the implementation of a substantial number of mesh routers, thereby substantiating the efficacy of the proposed method in conjunction with socially aware mobility models that emulate real-life community structures.

The second section of Table 3 presents a compilation of data concerning the number of state transitions (between MR and MC) that occurred in the nodes during the simulation for each scenario. As was the case in the initial section, the results are expressed with the minimum value, maximum, mean, and standard deviation, denoted by σ. As anticipated, scenarios such as Disaster Area and SWIM demonstrate a greater propensity for state transitions due to their elevated degree of mobility and dynamism, wherein nodes frequently undergo transitions between groups or communities. On average, 23 state changes occur during the simulation period in these scenarios, equivalent to a rate of 2.76 changes per minute. Conversely, the SMOOTH scenario exhibits the fewest alterations, with nodes predominantly relocating to proximate family neighborhoods. Consequently, the state change rate for this scenario averages 1.46 changes per minute. State changes directly impact node energy consumption. Temporary role assignments enable nodes to deactivate their routing functionalities intermittently, thereby averting protracted battery drainage.

The final part of Table 3 offers a summary of the mean number of edges in both reduced and full topologies (all nodes as MR) during the simulation. The C-A HC_BN topology control has been demonstrated to achieve edge reduction percentages ranging from 31% to 44%. This has been shown to result in enhanced network performance, as detailed in Section 5.

Table 3. Results of reduce topology backbone for the proposed C-A HC_BN method for all scenarios.

Mobility Model	Number of routers				Number of state changes				Average number of edges		
	Min.	Max.	Mean	σ	Min.	Max.	Mean	σ	All nodes as MR	C-A HC_BN	Difference
SWIM	34	48	40.28	2.93	8	35	23.36	6.14	356.54	232.65	34.58%
SLAW	31	44	36.34	3.36	5	28	15.96	5.79	541.14	320.31	40.77%
SMOOTH	34	49	41.43	2.86	0	32	12.2	6.65	356.09	245.93	30.52%
Disaster Area	31	44	36.33	2.73	6	40	22.77	7.52	486.65	284.31	41.47%
Map-based	33	46	37.66	3.15	2	26	13.35	5.34	480.03	267.76	43.97%
RWM	38	49	42.19	2.51	0	32	15.78	7.61	336.03	224.11	33.26%

5. Results and Discussion

In this section, an evaluation of the network's performance following the application of different topology control mechanisms was conducted. The topology control mechanisms evaluated included

no topology control, topology control without community awareness (2HC_BN), and community-aware topology control (C-A HC_BN), which is the proposed approach.

To assess these mechanisms, extensive simulations were performed using the ns-3 network simulator, considering both the reactive (on-demand) and proactive modes of the HWMP routing protocol. The network under consideration consists of 100 nodes that move according to various mobility models within an area of 1024 × 520 meters, as described in Section 4.1.

For each scenario, four snapshots were considered, with varying numbers of simultaneously active UDP data flows ranging from 10 to 40, independently simulated. All UDP data flows utilized 512-byte packet lengths with a 20 millisecond interarrival time. The transmission time was configured to 200 seconds, leading to the transmission of 10,000 packets in each peer-to-peer data flow.

To ensure the reliability of the results, 50 statistically independent executions were performed for each data flow scenario. The mean values of the results from the 200 runs for each case were subsequently calculated and averaged. The results are presented with a confidence interval of 95%.

5.1. Reactive Mode Results

In this section, an evaluation of the reactive mode of the HWMP routing protocol is conducted. A multifaceted evaluation approach is employed to assess network performance, encompassing several pivotal parameters. These include the rate of routing management messages, the total number of packets received successfully, the total number of forwardings per successfully received packet, the network efficiency as reflected by the packet delivery ratio (PDR), and the nodes' power consumption.

The evaluation process commences with an examination of the network in two distinct configurations: the first configuration is characterized by the absence of topology control, wherein all nodes function as routers, and the second configuration involves the implementation of topology control, utilizing the C-A HC_BN and 2HC_BN methods. In order to illustrate the advantages of applying topology control, the SWIM scenario is employed for this evaluation.

As demonstrated in Figure 4, the implementation of a topology control mechanism has been shown to result in substantial enhancements, including a reduction in routing messages (Figure 4(a)), a decrease in packet forwarding (Figure 4(b)), and an increase in successfully received packets (Figure 4(c)). Consequently, an enhancement in network efficiency is observed, as evidenced by an increase in the packet delivery ratio (Figure 4(e)). Conversely, due to the reduced number of routing messages and the decreased packet forwarding per received packet, a lower energy consumption is observed (see Figure 4(f)). The efficacy of implementing a topology control mechanism in a network can be demonstrated. The efficacy of the system is enhanced in all aspects, thereby mitigating prevalent issues such as packet collision and interference that are precipitated by the substantial density of nodes.

In future studies, the research team will focus on comparing metrics between 2HC_BN and C-A HC_BN. This will allow them to ascertain the impact of considering community structure in the topology control mechanism.
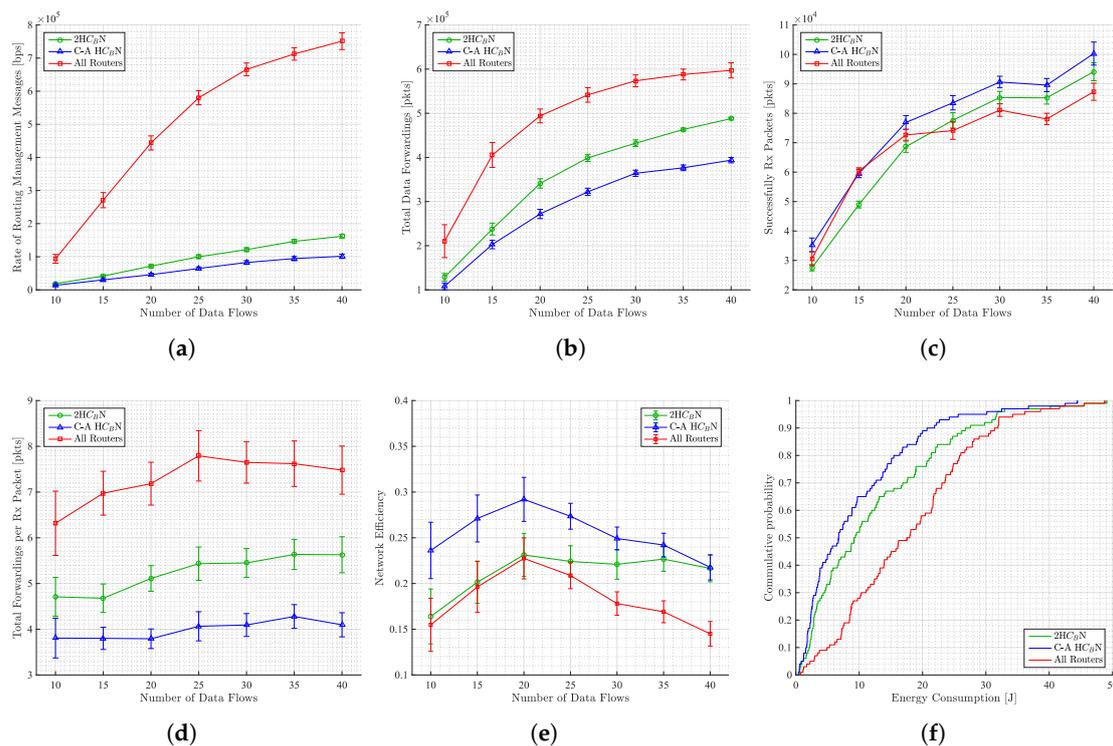
Figure 4. Results for all routers, and for $2HC_BN$ and C-A HC_BN topology control mechanisms for SWIM scenario. (**a**) Rate of routing management messages. (**b**) Total data forwardings. (**c**) Total number of successfully received packets. (**d**) Total data forwardings per successfully received packet. (**e**) Network efficiency in terms of PDR. (**f**) Nodes energy consumption CDF for 20 active flows.

5.1.1. Rate of Routing Management Messages

In this subsection, the average rate of routing management messages concerning the number of data flows across all scenarios considered is examined, as illustrated in Figure 5. As predicted, an escalation in traffic load—that is to say, the quantity of data flows—results in an augmented rate of routing messages, particularly in the context of evaluating an on-demand routing protocol.

It is imperative to underscore that this diminution in routing messages exerts a direct influence on energy consumption within the network. This reduction is primarily attributed to the fact that nodes that are not selected as routers do not transmit routing management messages.

It is noteworthy that in the map-based scenario (see Figure 5(**e**)), both topology control mechanisms generate a comparatively low rate of routing messages (less than 60,000 packets) in contrast to the other scenarios. This phenomenon is primarily attributable to the spatial distribution of the nodes. In a map-based model, nodes predominantly move along linear paths, such as streets and sidewalks. This results in fewer dense regions compared to open areas, such as parks or shopping centers. Consequently, path resolution requires fewer routing messages.

As illustrated in Table 5, the proposed method, C-A HC_BN, has been demonstrated to achieve an average percentage reduction in routing messages when compared to the previous proposal, $2HC_BN$, in a range of scenarios. This enhancement ranges from 17.64% in the map-based scenario to a substantial 38.29% in the SWIM scenario.
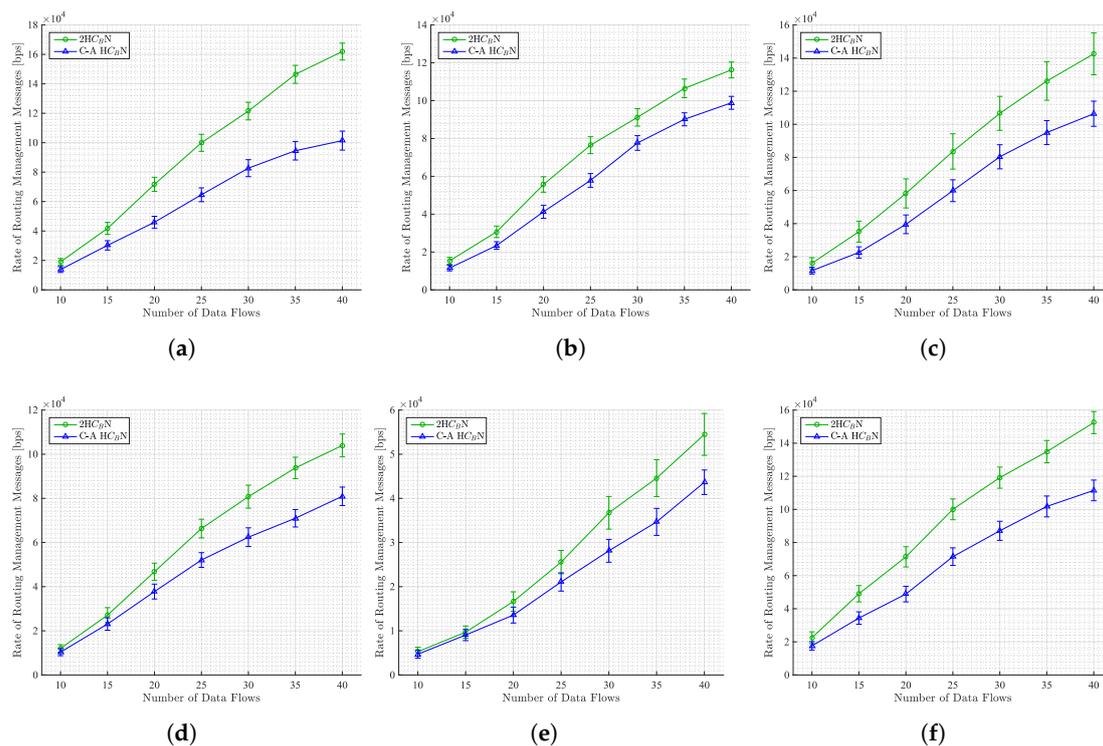
Figure 5. Average rate of routing management messages as a function of traffic load, for all scenarios considered. (**a**) SWIM scenario. (**b**) SLAW scenario. (**c**) SMOOTH scenario. (**d**) Disaster Area scenario. (**e**) Map-based scenario. (**f**) RWM scenario.

5.1.2. Total Data Forwardings

In this subsection, an analysis is conducted of the total number of data forwardings in all scenarios considered. As illustrated in Figure 6, the results for each scenario are presented as a function of traffic load.

As anticipated, with rising traffic load (number of data flows), the aggregate number of data transmissions concomitantly rises. This phenomenon aligns with the operational characteristics of on-demand routing protocols, which are designed to address data transmission demands by initiating route discovery and maintenance processes.

It is imperative to acknowledge that the implementation of topology control mechanisms leads to a decrease in the aggregate number of data forwardings. This decline is primarily attributable to the reduced selection of nodes as routers within the network, resulting in diminished route discoveries and data relay operations.

The specific impact of topology control methods, such as C-A HC_BN and 2HC_BN, on the total data forwarding can be observed in Figure 6. These methods can also be compared with the scenario without topology control. This reduction in data transmission serves to illustrate the enhanced efficiency of the network with the implementation of topology control mechanisms, thereby further underscoring the merits of these mechanisms in the management of data transmissions.
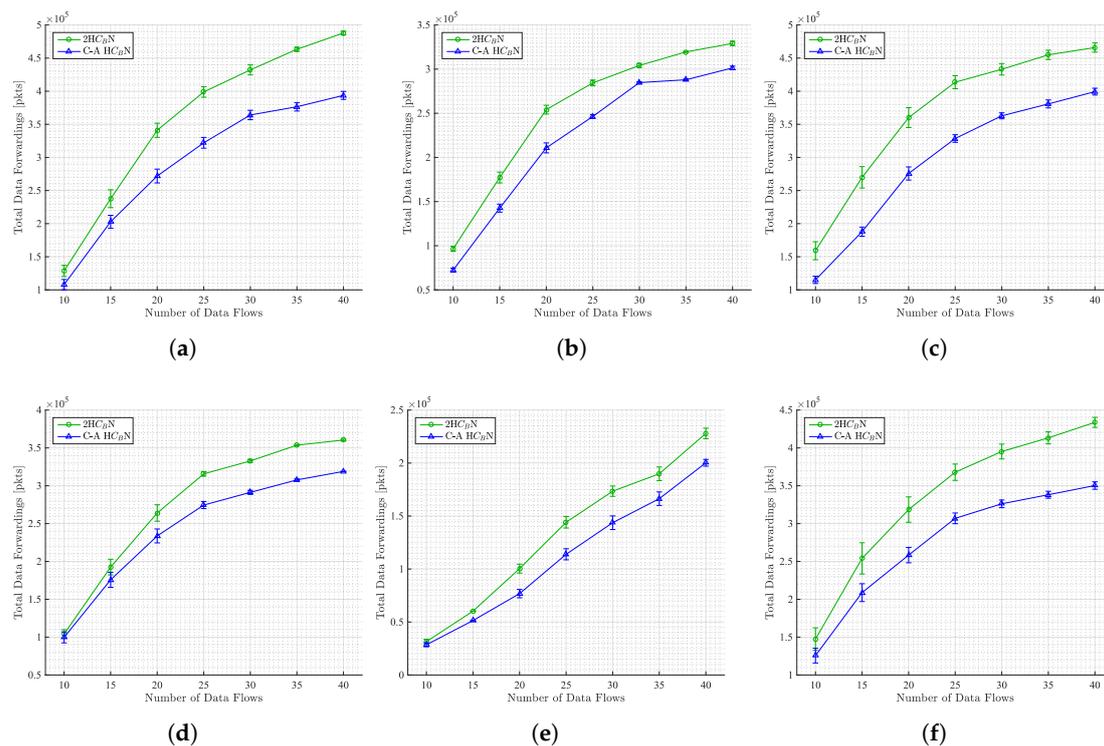
Figure 6. Total data forwardings as a function of traffic load, for all scenarios considered. (**a**) SWIM scenario. (**b**) SLAW scenario. (**c**) SMOOTH scenario. (**d**) Disaster Area scenario. (**e**) Map-based scenario. (**f**) RWM scenario.

5.1.3. Successfully Received Packets

In this subsection, the number of successfully received packets is examined as a function of the number of active data flows across all scenarios. The results are presented in Figure 7.

The observed trend in the number of successfully received packets is consistent with network saturation. As the number of active data flows increases, the network approaches a state of saturation, resulting in a plateau in the number of received packets. The plateau effect is particularly evident in scenarios involving 40 simultaneous flows.

A substantial enhancement in the number of successfully received packets has been observed in a variety of scenarios, including SWIM, SLAW, Map-based, and RWM (see Figures 7(**a**), 7(**b**), 7(**e**) and 7(**f**)). The efficacy of these enhancements can be attributed to the implementation of topology control methods, such as C-A HC_BN and $2HC_BN$.

However, for the scenarios of the SMOOTH and Disaster Area (see Figures 7(**c**) and 7(**d**)), there is negligible to no substantial enhancement in the number of successfully received packets. The negligible variations observed in these scenarios are within the confidence intervals, indicating that the topology control methods have minimal impact in these specific scenarios. The Disaster Area scenario, distinguished by its dense regions, may exhibit a comparatively diminished capacity for improvement as a result of its distinct characteristics.

In essence, the implementation of topology control mechanisms has been demonstrated to enhance the network's efficiency by increasing the number of successfully received packets in various scenarios. However, the impact of these mechanisms varies depending on the characteristics of the specific scenario.
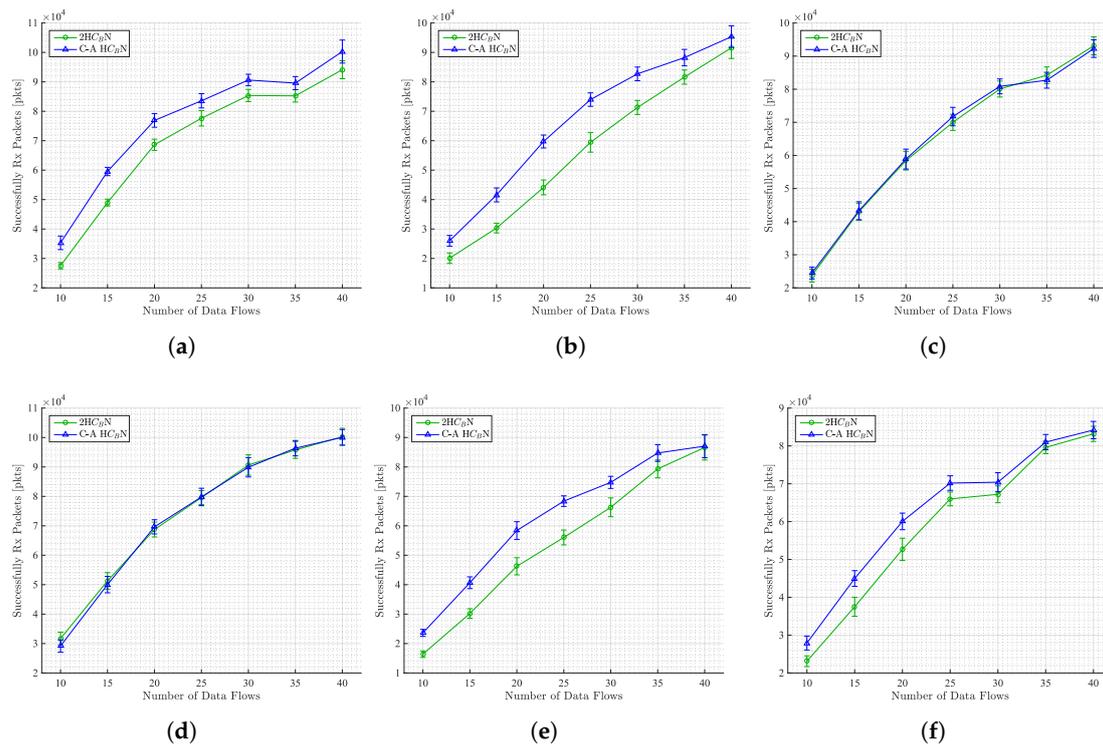
Figure 7. Total number of successfully received data packets as a function of traffic load, for all scenarios considered. (**a**) SWIM scenario. (**b**) SLAW scenario. (**c**) SMOOTH scenario. (**d**) Disaster Area scenario. (**e**) Map-based scenario. (**f**) RWM scenario.

5.1.4. Total Data Forwardings per Successfully Received Packet

In this subsection, the relationship between the number of forwarded packets and the number of packets successfully received in all scenarios is explored (see Figure 8). It has been observed that the proposed method C-A HC_BN requires a smaller number of forwarded packets compared to the previous method $2HC_BN$.

In the majority of scenarios, there is an increasing trend in the number of forwarded packets as the number of data flows increases. This phenomenon can be attributed to an increase in packet retransmissions, which, in turn, results in a higher number of collisions within the network. This trend persists until a saturated state is attained, which typically occurs between 25 and 30 flows for the majority of mobility models. However, in the SLAW scenario (see Figure 8(**b**)), an early saturation state is observed, occurring at 20 data flows. This phenomenon can be attributed to the relatively high number of edges in the reduced topology for the SLAW scenario, as evidenced in Table 4. This results in increased interference and a higher number of forwardings per received packet.

As presented in Table 5, the proposed method C-A HC_BN exhibits a mean percentage reduction in data forwardings per successfully received packet compared to the previous method $2HC_BN$ for each mobility model. As previously discussed, the Disaster Area scenario demonstrates a comparatively diminished decrease in comparison to alternative scenarios, primarily attributable to its high degree of density.

In general, the proposed topology control method C-A HC_BN has been demonstrated to be effective by reducing the number of forwarded packets per successfully received packet, resulting in improved network efficiency. However, the extent of this improvement varies depending on the specific characteristics of the scenario.
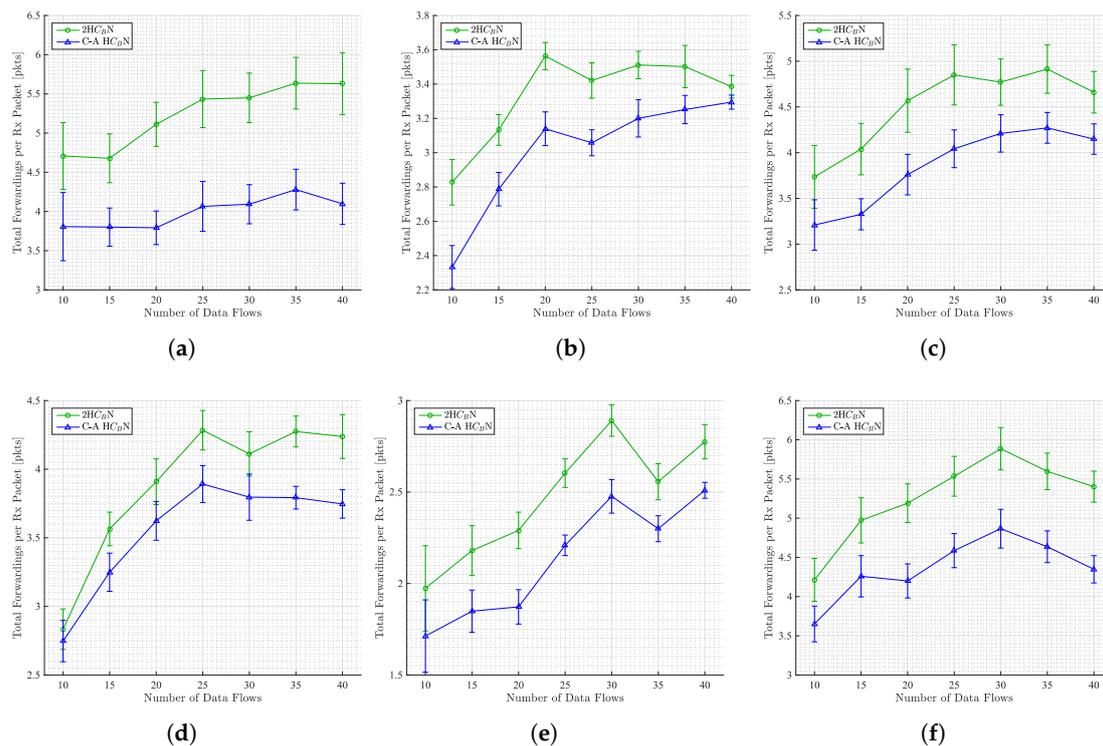
Figure 8. Total data forwardings per successfully received packets as a function of traffic load, for all scenarios considered. (**a**) SWIM scenario. (**b**) SLAW scenario. (**c**) SMOOTH scenario. (**d**) Disaster Area scenario. (**e**) Map-based scenario. (**f**) RWM scenario.

Table 4. Average number of edges in topologies for 500 second simulation.

Scenario	All Routers	C-A HC_BN
SWIM	356.54	232.65
SLAW	541.14	320.31
SMOOTH	356.09	245.93
Disaster A.	486.65	284.31
Map-based	480.03	267.76
RWM	336.03	224.11

5.1.5. Network Efficiency in Terms of Packet Delivery Ratio

In this subsection, the network's efficiency is examined in terms of the packet delivery ratio (PDR), a pivotal performance metric calculated by dividing the number of successfully received packets by the total number of transmitted packets. A parallel can be drawn between the trends observed in PDR and those depicted in Figure 7.

As demonstrated in Figure 9, the findings underscore substantial enhancements in PDR for SWIM, SLAW, Map-based, and RWM scenarios across all traffic loads. Conversely, the SMOOTH and Disaster Area scenarios (illustrated in Figures 9(**c**) and 9(**d**)) exhibit minimal to no efficiency enhancements. This observation is reinforced by the data in 5 (sixth column), which confirms the insignificant improvements in these scenarios. This outcome is anticipated, as the PDR metric is intrinsically associated with the number of successfully received packets (as discussed in Section 5.1.3), where no substantial enhancements were observed for these scenarios.

It is noteworthy that columns 4 and 6 in Table 5 exhibit identical improvement values, a consequence of the direct proportionality between PDR and the number of successfully received packets. In general, the proposed topology control method C-A HC_BN has been shown to enhance network efficiency, particularly in scenarios characterized by community structure, such as SWIM, SLAW,

Map-based, and RWM. However, the extent of the improvement in question is subject to variation depending on the characteristics inherent to particular scenarios.
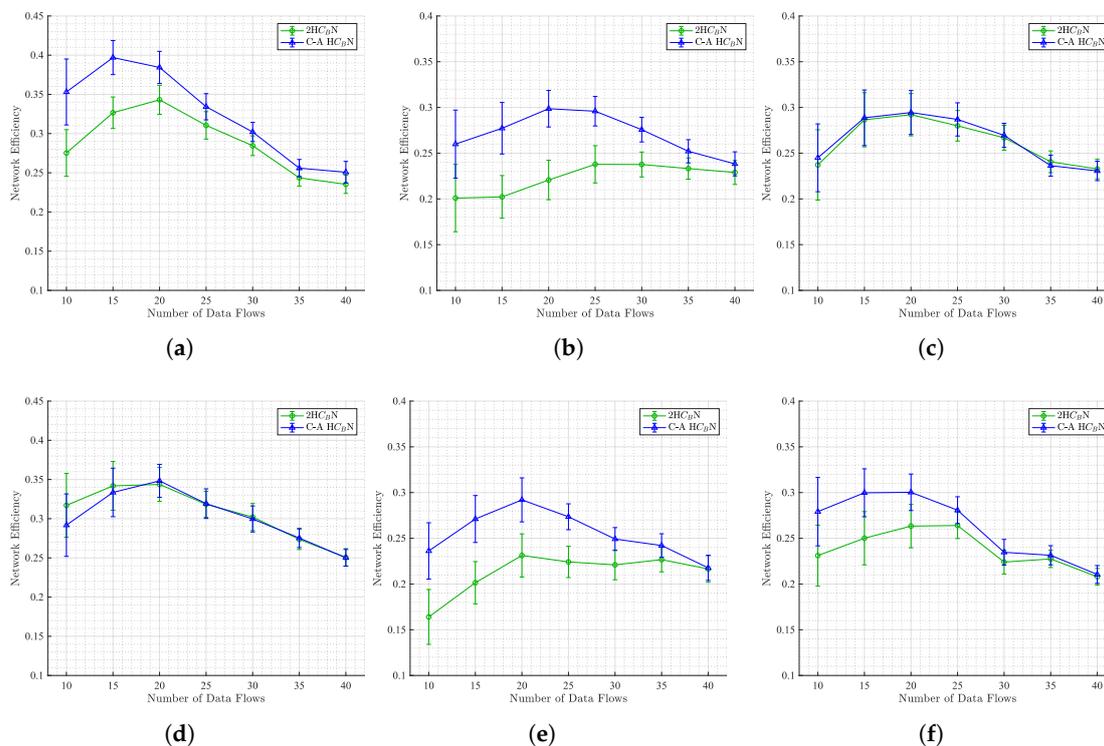

Figure 9. Network efficiency in terms of PDR as a function of the traffic load, for all scenarios considered. (**a**) SWIM scenario. (**b**) SLAW scenario. (**c**) SMOOTH scenario. (**d**) Disaster Area scenario. (**e**) Map-based scenario. (**f**) RWM scenario.

5.1.6. Energy Consumption

The enhanced efficiency of the network, in conjunction with substantial decreases in the transmission of routing messages and the forwarding of packets, results in quantifiable energy consumption reductions throughout the network. In accordance with the approach delineated in [72], we assess energy consumption employing the model established in [81].

To facilitate a comprehensive analysis, the intermediate operating point of 20 active data flows is the focal point of this study. At this stage, the network is neither overload-prone nor operates under negligible traffic loads. In order to facilitate a more profound comprehension of this parameter, the average reduction of network energy consumption when employing the C-A HC_BN method is presented in Table 5, in comparison to the $2HC_BN$.

Specifically, in the SLAW scenario, approximately 70% of the nodes consume less than 7 Joules under both methods. However, the remaining 30% of the nodes demonstrate energy savings when using the C-A HC_BN method compared to $2HC_BN$. It is noteworthy that the Map-based scenario achieves the lowest energy consumption. This is due to the limited volume of routing messages and packet forwarding, which reduces energy-intensive operations across the network.

Table 5. Average improvements with the C-A HC_BN method compared to $2HC_BN$, for reactive mode.

Mobility Model	Reduction of routing messages	Reduction of data forwardings	Increase in received packets	Reduction of forwardings per successfully received packet	Increase in network efficiency in terms of PDR	Reduction of network energy consumption (20 data flows)
SWIM	38.29%	17.73%	10.63%	23.58%	10.63%	22.54%
SLAW	20.55%	14.23%	17.25%	9.96%	17.25%	13.93%
SMOOTH	28.35%	21.26%	0.78%	14.56%	0.78%	17.19%
Disaster A.	19.81%	10.64%	-1.43%	8.42%	-1.43%	14.69%
Map-based	17.00%	15.77%	16.19%	13.68%	16.19%	35.40%
RWM	27.19%	17.56%	8.50%	16.85%	8.50%	24.99%

5.2. Proactive Mode

In this section, the proactive mode of the HWMP routing protocol was examined. In this operational mode, one or more mesh stations are designated as roots, thereby serving as gateways for communication within the network. These root nodes facilitate the creation and maintenance of distance vector trees.

In order to enhance network performance, root stations are strategically placed in the geography of the network. To assess the impact of this configuration, multiple simulations were conducted with varying numbers of root stations—ranging from one to three—using the same configurations as in the previous reactive mode evaluations.

5.2.1. Rate of Routing Management Messages

For this parameter, a constant traffic load of 25 data flows is utilized, divided into two parts. The first part involves downloading 20 streams from root stations to randomly selected nodes, and the second part involves uploading 5 streams from randomly selected nodes to root stations.

As illustrated in Figure 10, the results demonstrate variations in the rate of routing management messages, contingent on the number of root stations present in all scenarios. Each mobility model exhibits a distinct pattern; however, a common trend is a reduction in routing messages with the C-A HC_BN method compared to $2HC_BN$.

As illustrated in Table 6, the second column provides a quantitative summary of the average percentage reduction in this parameter when comparing C-A HC_BN with $2HC_BN$. It is evident that the reduction percentage is less significant for the SLAW and disaster area scenarios, while the other scenarios display substantial reductions. This finding indicates the effectiveness of the C-A HC_BN method.

5.2.2. Network Efficiency in Terms of Packet Delivery Ratio

Network efficiency, measured in terms of Packet Delivery Ratio (PDR), is assessed with 25 data flows (similar to 5.2.1) and varying numbers of configured root stations: one, two, and three. As illustrated in Figure 11, the results are presented for all scenarios.

In most cases, a trend emerges in which an increase in the number of root stations leads to improved network efficiency. This outcome is attributed to the more balanced distribution of the network load between the gateways, resulting in fewer packet collisions and higher network efficiency.

As illustrated in Table 6 (3rd column), the mean enhancement in network efficiency attained by the C-A HC_BN method in comparison with $2HC_BN$ is evident. While the majority of scenarios demonstrate only marginal improvements, the map-based scenario is noteworthy with a substantial 34.02% enhancement.
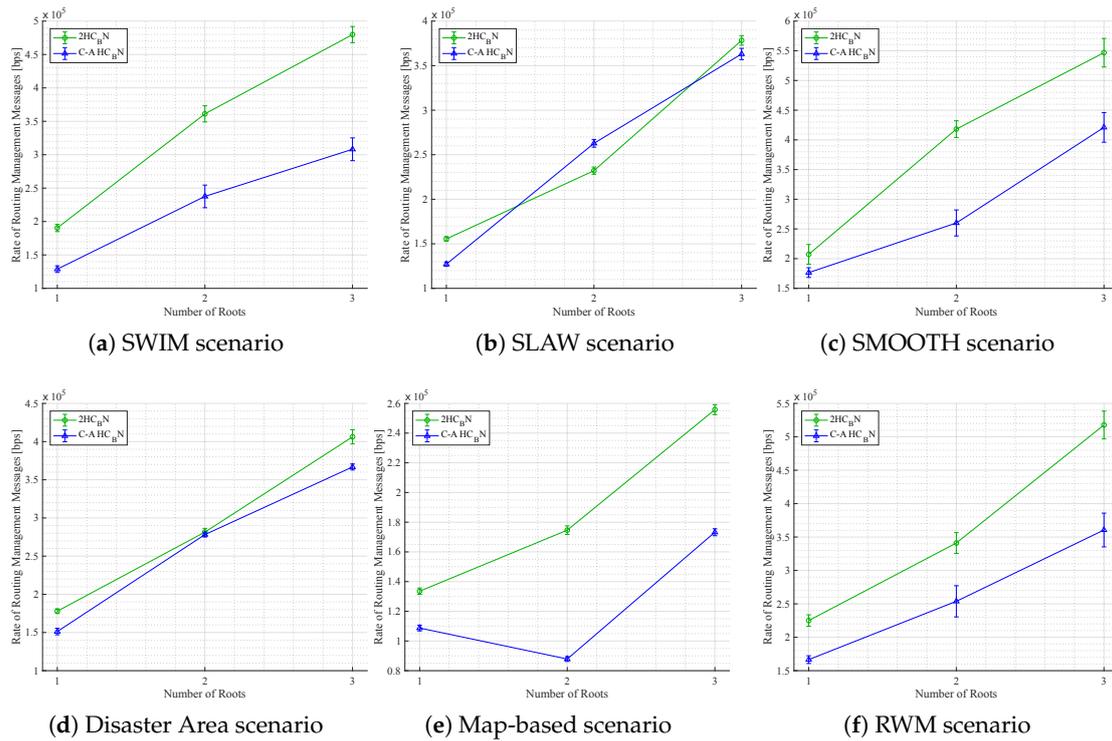
Figure 10. Average rate of routing management messages as a function of the number of root stations, for all scenarios considered.
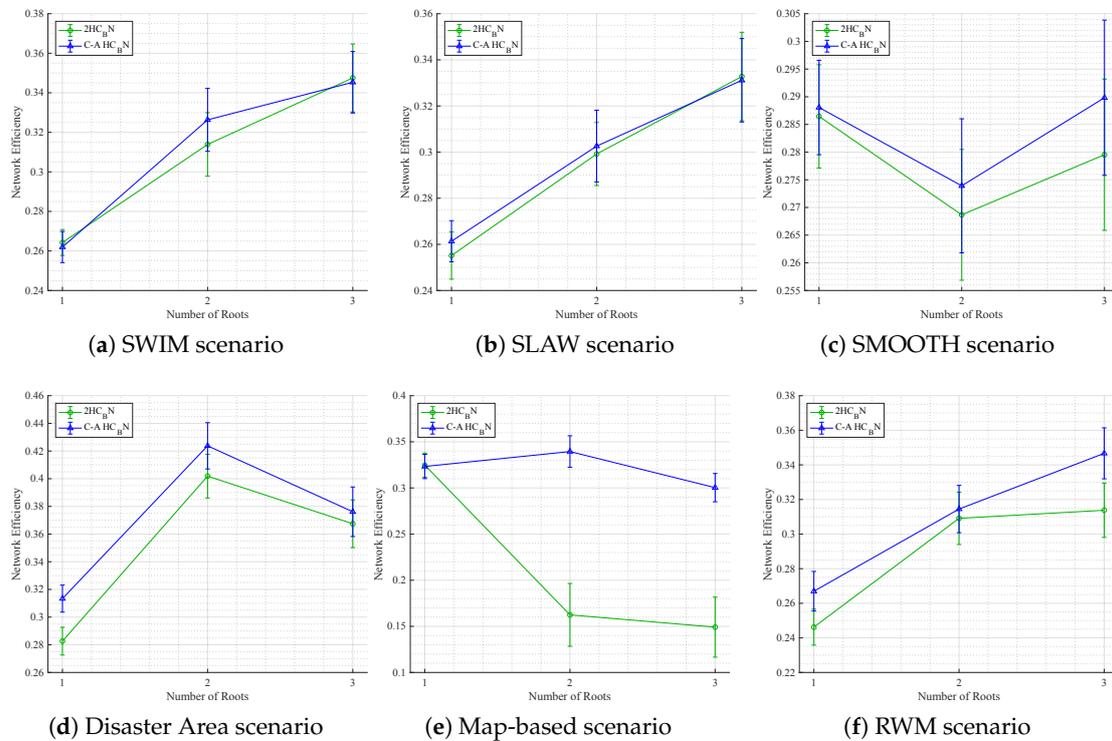

Figure 11. Network efficiency in terms of PDR as a function of the number of root stations, for all scenarios considered.

5.2.3. Energy Consumption

For the analysis of energy consumption, we introduce three configured root stations and simulate 75 data flows (60 downloads and 15 uploads) to ensure representative results. To provide a quantitative

perspective, Table 6 presents the average reduction in the overall energy consumption of the network achieved by C-A HC_BN compared to $2HC_BN$ in the fourth column. The fifth column provides these values specifically for non-root stations. It is clear to see that for all mobility models, energy consumption is reduced.

Table 6. Average improvements with the C-A HC_BN method compared to $2HC_BN$, for proactive mode.

Mobility Model	Reduction of routing messages	Increase in network efficiency in terms of PDR	Reduction of energy consumption with 3 root stations and 75 active flows	
			All nodes	non-root station only
SWIM	34.11%	0.77%	15.26%	6.92%
SLAW	3.01%	1.00%	2.12%	1.42%
SMOOTH	25.20%	2.01%	7.16%	3.64%
Disaster A.	8.61%	5.76%	9.16%	8.66%
Map-based	33.52%	34.02%	12.54%	6.86%
RWM	27.31%	6.32%	14.34%	11.40%

6. Conclusions

This paper introduces a community-aware topology control mechanism, C-A HC_BN, for wireless mesh networks, using centrality metrics. The mechanism identifies crucial nodes within communities (determined by the centrality of the betweenness) and those that facilitate communication between communities (identified by the centrality of the bridging), forming the backbone of the network. The efficacy of C-A HC_BN was assessed in six distinct scenarios employing various mobility models, yielding an average reduction in active edges in the network ranging from 30.52% to 41.47%.

When subjected to low traffic loads, C-A HC_BN demonstrated enhanced network performance in both reactive and proactive modes of the HWMP mesh routing protocol in comparison to the previous method, $2HC_BN$. This configuration has been demonstrated to reduce the number of routing messages and forwardings, thereby enhancing network efficiency and reducing energy expenditure. These results substantiate the efficacy of C-A HC_BN in realistic wireless mesh network scenarios.

Despite the utilization of a centralized approach in the present proposal, future endeavors may involve the exploration of distributed community detection algorithms and centrality calculation methods. Furthermore, the incorporation of novel metrics, such as remaining node energy, device type, or geographical location, into centrality calculations has the potential to enhance the efficacy and adaptability of the mechanism.

Abbreviations

The following abbreviations are used in this manuscript:

WSN	Wireless Sensor Network
IoT	Internet of Things
WSN	Wireless Sensor Network
WMN	Wireless Mesh Network
HWMP	Hybrid Wireless Mesh Protocol
CDS	Connected Dominating Set
RWM	Random Waypoint Mobility
SWIM	Small World In Motion
SLAW	Self-Similar Least-Action Human Walk
SMOOTH	Simplified Mobility Model for Human Walks
IL	Incident Location
PWT	Patient Waiting Area
CCS	Casualties Clearing Station
TOC	Technical Operation Command
MSLAW	Map-Based Self-Similar Least-Action Human Walk
C_B	Betweenness Centrality
$intraC_B$	Intra-Centrality
$interC_B$	Inter-Centrality
C_{Brid}	Bridging Centrality
C-A H$IntraC_B$N	Community-Aware Highest Betweenness Intra-Centrality Neighbor
C-A HC_BN	Community-Aware Highest Betweenness Centrality Neighbor
2HC_BN	2 Highest Betweenness Centrality Neighbors
BC	Bridging Coefficient
MR	Mesh Router
MC	Mesh Client
PDR	Packet Delivery Ratio
UDP	User Datagram Protocol
SUMO	Simulation of Urban Mobility

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