Comparative Analysis of Opp-IoT Routing Protocols Under Varying Node Density

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Abstract: The Internet of Things increasingly operates in environments where stable, infrastructure-based connectivity cannot be assumed: environmental sensing, vehicular and drone networks, industrial automation, healthcare wearables, and disaster-response scenarios among them. Opportunistic IoT networks (Opp-IoT) apply the store-carry-forward paradigm of opportunistic networking to such settings, accepting delay as a structural feature in exchange for delivery where conventional schemes fail. Despite a rich routing-protocol literature, the absence of standardised, density-aware comparison has produced inconsistent guidance for protocol selection — a particular problem for IoT, where deployments span densities from below one device per square kilometre in remote sensing to several hundred in industrial and urban contexts. This paper presents a controlled simulation study of nine routing protocols from the six dominant Opp-IoT families: flooding-, forwarding-, probability-, knowledge-, and social-relationship-based, plus hybrid. Using the ONE simulator on a 4500 × 3400 m² scenario over ten hours, node density was varied from 50 to 500 nodes and evaluated against eight Quality-of-Service metrics. Spray-and-Wait and FRESH dominate across the density spectrum with complementary strengths: Spray-and-Wait optimises delivery rate and overhead, FRESH minimises drops, latency, and buffer occupancy. For IoT deployments, where reliability, latency, and resource economy are paramount, FRESH is recommended as the default routing protocol.

Keywords: Opp-IoT, opportunistic IoT networks, routing protocols, node density, ONE simulator, QoS, delay-tolerant networking, Internet of Things.

1. Introduction

IoT applications have outgrown the assumption of stable, gateway-based connectivity. Remote environmental sensing, underwater monitoring, vehicular networks, drone swarms, post-disaster reformations, body-area sensors with intermittent uplink, and urban-scale device populations all operate in regimes where end-to-end paths may not exist at any instant. Routing schemes built on the connected-graph assumption — AODV, DSR, DSDV, TCP/IP — degrade sharply or fail outright in such conditions [1][2]. Opp-IoT addresses this regime by adopting a store-carry-forward paradigm in which intermediate devices buffer messages until contact opportunities permit further forwarding. Inheriting from delay-tolerant networking and opportunistic mobile ad hoc work, Opp-IoT treats high delay as structural rather than defective, trading instantaneous for eventual delivery. The model is well-suited to the constrained, mobile, short-range devices that dominate IoT [3][4]. The Opp-IoT routing literature is rich but fragmented. Studies typically examine non-overlapping protocol subsets under non-uniform conditions, with different simulators, mobility models, and metric inventories. Density is a particularly under-treated variable despite being essential: IoT deployments span from below one device per square kilometre to several hundred, and protocols that excel in one regime can collapse in another. This paper contributes a unified, density-controlled evaluation of nine Opp-IoT routing protocols spanning all six major families, in the ONE simulator under a fixed parameter envelope. Eight QoS metrics are reported and interpreted both in absolute terms and against the operational priorities of IoT deployment. Section 2 reviews foundations; Section 3 describes the protocols; Section 4 the methodology; Section 5 the results; Section 6 concludes.

2. Background

2.1 Opp-IoT: Opp-IoT is an integrated approach between opportunistic networking, delay-tolerant networking and constrained-device IoT. Instead of the traditional gateway topologies, the members of the Opp-IoT create new associations and move data from one to another across periods of disconnection, in their own buffers [6][7][8]. The compromises are clear – tolerances for high delays, asymmetric data rates, and intermittent connections, at the expense of significant buffer sizes and energy consumption at participating devices, and the security risks associated with using opportunistic intermediates that can drop, delay, and subject transit data to scrutiny[9].

2.2 Node Density: In this section, the density variable is treated as a first-class variable. No one protocol fits the bill for IoT deployments. Networks of remote environmental sensing and acoustic sensors work at less than 5 nodes/km2. The number of dense industrial-IoT installations, urban vehicular networks and crowd-sensing can be of several hundreds. In between are healthcare IoT, smart-warehouse deployments or networks after disasters. Guide behaviour that is successful in one regime may fail in others, thus making density-aware guidance a practical requirement [10][11].

2.3 Protocol Categories: Six categories dominate the Opp-IoT routing literature. *Flooding-based protocols* replicate aggressively, trading overhead for delivery. *Forwarding-based* use a single-copy discipline that minimises overhead at the cost of delay. *Probability-based* use encounter history to estimate delivery likelihood. *Knowledge-based* maintain richer state about future or global connectivity. *Social-relationship-based* exploit recent-encounter information or social topology. *Hybrid* protocols combine elements of more than one family. The nine protocols evaluated below include at least one representative from each [12].

3. Routing Protocols Examined

a) *Epidemic*(Flooding-based) treats data propagation as analogous to infectious-disease spread: any encounter between an "infected" custodian and a susceptible neighbour leads to replication, until the message reaches the destination. Simple, but high in overhead and buffer pressure [13].
b) *Spray-and-Wait* (Flooding-based) caps the replica count. In the *spray* phase, the source distributes a fixed number of copies; in the *wait* phase, holders wait to meet the destination directly [14].
c) *Direct Delivery* (forwarding-based) is the minimum-overhead extreme: the source holds the message until it meets the destination itself. Zero overhead, but delivery is hostage to encounter probability [15].
d) *First Contact* (forwarding-based) forwards each message to the first node encountered, recursively. Random with respect to topology, easy to implement, but poor on delivery and latency in non-trivial networks [16].
e) *PRoPHET* (probability-based) maintains a delivery predictability P(a,b) for each destination, updated on each encounter, aged between encounters as P(a,b) = P(a,b)^{P{old}}, and propagated transitively across shared contacts. Forwarding favours higher-predictability custodians [17].
f) *MaxProp* (probability-based) prioritises both messages-to-drop and messages-to-forward using a cost function based on inter-node delivery probabilities and historical data. Newer and lower-hop messages receive higher priority. Explicitly targets latency and delivery rate [18].
g) *Epidemic Oracle* (knowledge-based) augments Epidemic with a knowledge base of future connectivity; forwarding occurs only when delivery probability is judged sufficient. The knowledge requirement makes it most attractive in sparse, predictable deployments[19].
h) FRESH (social-relationship-based) sends messages to nodes that most recently received the target. Discovery is broken up into small searches as opposed to being a flood.This leaves a lower level of overhead, without loss of delivery quality [20].

i) *In RAPID (hybrid), routing is considered as resource allocation. A utility function assigns a value to each message that represents the value that it would bring to a specified utility to the sender, which is usually a measure of delay* [21].

4. Simulation Methodology

The simulator, the ONE (Opportunistic Network Environment) simulator was selected. Based on the survey data, it can be seen that the ONE simulation platform is responsible for around 62% of the simulation-based research in the field of Opp-IoT and opportunistic-networking, due to its support for mobility modelling, post-processing and its scalable implementation in Java. Lower layer restrictions do not matter for QoS level routing comparison. A fixed area of 4500 × 3400 m² (15.3 km²) was used for the simulation for 10 hours. The movement of the nodes was done using the Random Waypoint model with velocities between 0.5 and 1.5 m/s. Dual-radio IoT hardware came with each node: Bluetooth (250 kbps, 10 m range, 32 s scan interval) and Wi-Fi (500 kbps, 10 m range, 64 s scan interval). Message size: 500 KB–1 MB; TTL: 240 min; buffer: 5 MB; update interval: 0.1 s; warm-up: 1800 s. Only one parameter (the number of nodes) was changed and varied from 50 to 500 by increments of 50. The metrics collected were: number of nodes participating (controlled), Messages Delivered, Messages Dropped, Delivery Probability, Overhead Ratio, Average Latency, Average Hop Count, and Average Buffer Time. These are grouped together under efficiency, reliability, and resource usage[4][5].

5. Results and Analysis

The results are displayed in grouped bar charts across four density levels (50, 200, 350, 500 nodes) for all nine protocols. The complete sweep range of 50 – 500 was simulated.

5.1 Message Delivery: FRESH led delivery in low-to-moderate densities (< 500 nodes) before Spray-and-Wait surpassed it at 500 nodes and onwards (Figure 1). PRoPHET was competitive in the 100–250 range. MaxProp caught up to the front of the pack above 250. First Contact and Direct Delivery followed around.

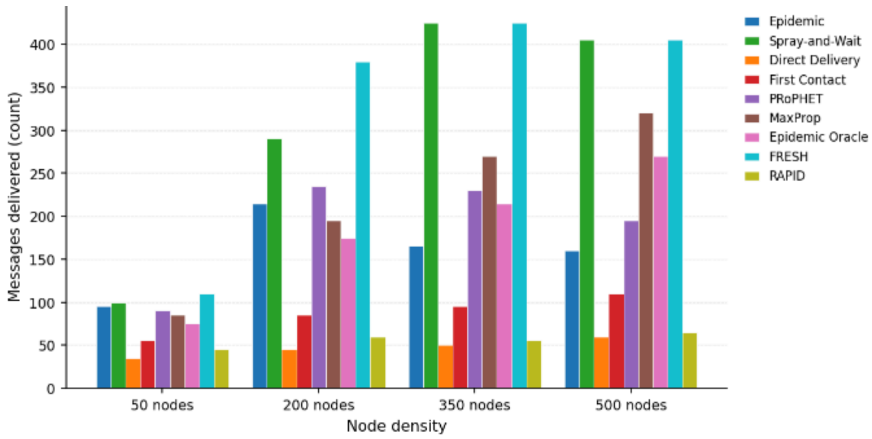

Figure 1: Messages delivered vs. node density

5.2 Message Drops: Drops revealed the cost of aggressive flooding (log scale - Figure 2). Epidemic had the largest numbers of drops throughout the sweep, while PRoPHET led at 500 nodes. Conservative replication resulted in no drops on any density for FRESH nor any above 150 nodes for Direct Delivery. IoT energy constrained, protocol with minimal drop, minimal wasted radio expenditure***.***

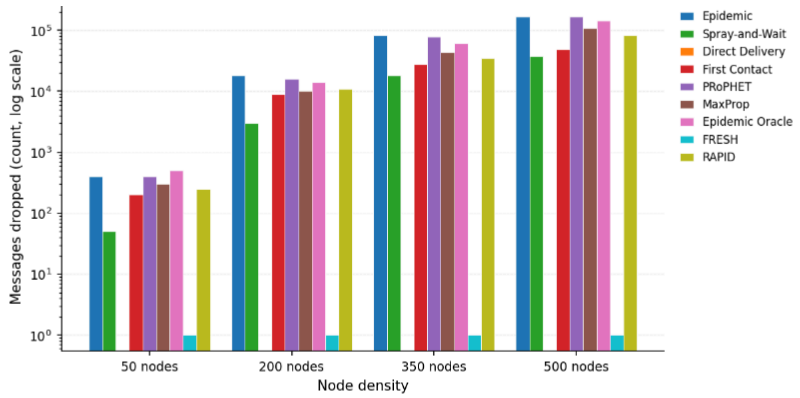

Figure 2: Messages dropped vs. node density

5.3 Delivery Probability: Delivery probability monitored the delivery-count trend (Figure 3). FRESH led from 50 to 270 nodes; Spray-and-Wait led from 270 to 500. The structural meaning of the crossover is worth emphasizing: When the information about encounters is informatively scarce, FRESH is most successful, while Spray-and-Wait is most successful with increased contact frequency.

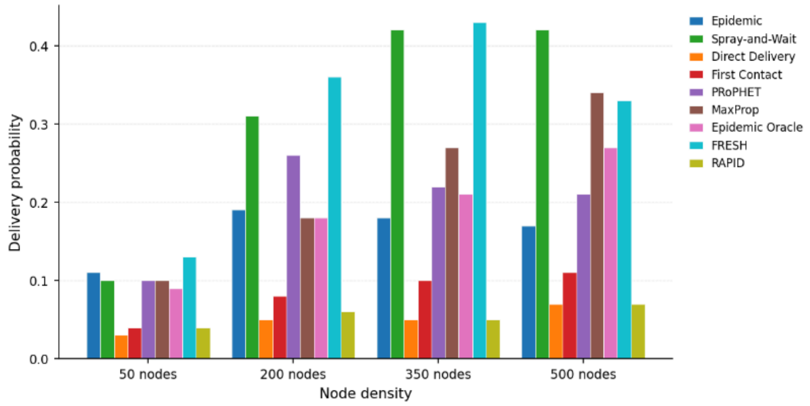

Figure 3: Delivery probability vs. node density

5.4 Overhead: The zero overhead by construction was the only value for Direct Delivery (Figure 4). Spray-and-Wait was second in all densities. Epidemic Oracle had the largest overhead at low densities (≤ 150 nodes) while Epidemic and PRoPHET were close behind. FRESH was in the low overhead tier until 200 nodes, and then increased moderately.

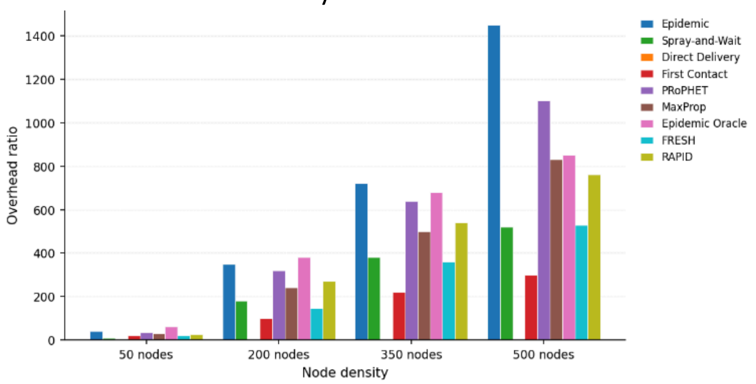

Figure 4: Overhead ratio vs. node density

5.5 Average Latency: For Epidemic, the lowest latency was 50 nodes and it dropped significantly with density (Figure 5). MaxProp and RAPID values were always high. With this recency-driven custodian selection – and especially for latency-sensitive applications like health monitoring and industrial control, where the Internet of Things is increasingly gaining traction – FRESH significantly outperformed the others in terms of average latency, recording the lowest results over the entire sweep.

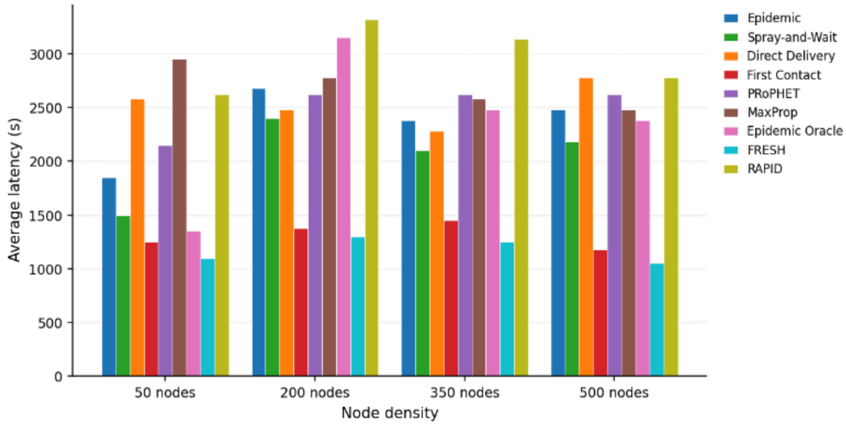

Figure 5: Average latency vs. node density

5.6 Hop Count: Spray-and-Wait and MaxProp had the lowest average hops, behind Direct Delivery, which is guaranteed to be in one hop by design, but in front of PRoPHET (Figure 6). The biggest required for Epidemic Oracle was the highest. The number of hops in the "fresh" system increased linearly as the density increased. In the case of energy concern per hop, there is a clear benefit of low hop count protocols.

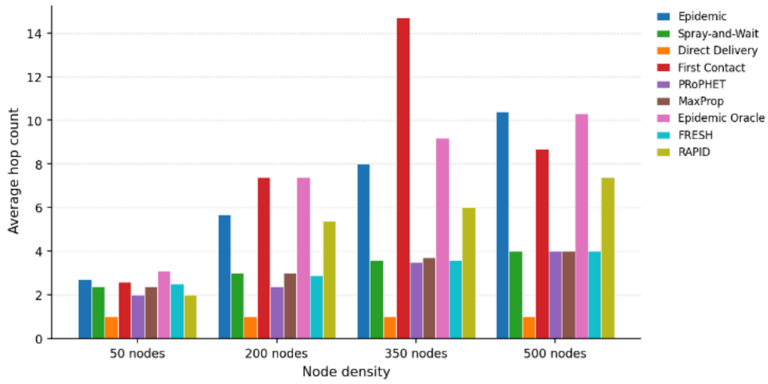

Figure 6: Average hop count vs. node density

5.7 Buffer Time: The buffer time was reduced to under 150 nodes for Direct Delivery with FRESH being a close second throughout the range (Figure 7). The buffer times decreased with increasing density for most protocols, but Spray-and-Wait was the significant exception, where increasing density meant increasing buffer time. If buffer occupancy represents energy consumption, then low buffer time is preferred in IoT scenarios.

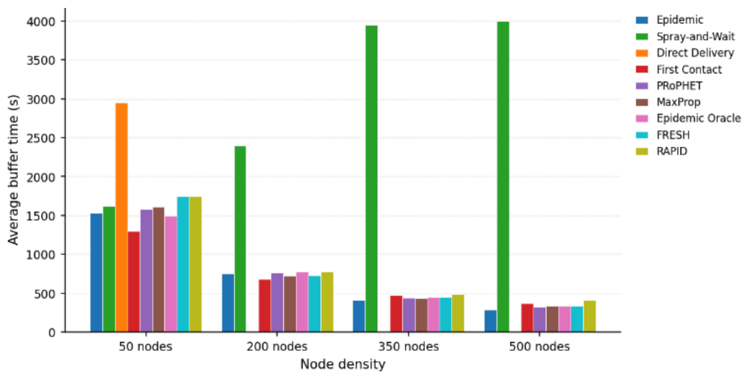

Figure 7: Average buffer time vs. node density

5.8 Recommendation: There were two overall leaders: Spray-and-Wait and FRESH. Spray-and-Wait outperformed FRESH in terms of messages delivered, messages delivered probability, overhead, and hop count; FRESH outperformed Spray-and-Wait in terms of messages dropped, latency, and buffer time. Drop rate, latency, and buffer occupancy are the concerns for typical IoT deployments where energy constraints are very important, latency is frequently critical, and the need for reliable delivery is crucial. On all three, FRESH leads. The advice: If overhead minimisation or sheer volume of delivery is the top priority, the answer is FRESH as the default routing protocol for Opp-IoT, and Spray-and-Wait as a competitive alternative.

6. Conclusion

This study examined nine representative Opportunistic Internet of Things (Opp-IoT) routing protocols across six families, and evaluated their performances under eight Quality of Service (QoS) metrics in a controlled experiment implemented in the ONE simulator. The only variable manipulated in the experiments was node density, which varied from 50 to 500 nodes. The performance of the protocols was evaluated in terms of node density (the total number of nodes that were present) and was compared with the performance of each protocol in terms of eight QoS metrics. Spray and Wait and FRESH were the best protocols. The results suggest that FRESH should be the preferred protocol, considering the characteristics of most IoT implementations. There are three possible routes for future research based on the results presented. First, the assessment should be extended to include energy consumption and security as primary metrics. Second, the range of protocols should be extended to capture Opp-IoT protocols augmented with machine learning and blockchain technologies. Third, the simulation should be tested with real IoT mobility patterns. Instead of Random Waypoint, a simulation with real movement patterns would replace the synthetic mobility.

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