

Original Research

Received 29 May 2026

Revised 18 July 2026

Accepted 08 August 2026

Natural Resources for Human Health 2026, Vol. 6 (14s): 954–964

KEYWORDS:

Mobile ad hoc networks; congestion control; load balancing; quality of service; route recovery; AOMDV.

An Adaptive Routing Framework for Load Balancing and Energy Efficiency in Wireless Sensor Networks

Priyanka Singh¹, Jgveer Singh², Mrs. Deepa P³, Mansi Bansal⁴, Preeti Saroj⁵, Maneesh Pant⁶, Bhupal Arya⁷

¹School of Computer Science and Artificial Intelligence, Galgotias University, Greater Noida, India

³Department of computer science and Engineering, M S Ramaiah University of Applied Sciences, Bangalore

⁴Department of computer science and Engineering, Institute of Innovation in technology and management, Janakpuri (New Delhi)

^{2,5,6,7}Department of Computer Science and Engineering, Galgotias University, Greater Noida, India

ABSTRACT: Wireless networks that operate without fixed infrastructure face a persistent challenge in sustaining reliable Quality of Service, largely because bandwidth stays limited, links break without warning, and packets can be lost mid-transit. When a network falls back on standard recovery methods after such a disruption, the cost usually shows up as drained battery reserves and slower data delivery, and this cost compounds as the node count rises. This work responds to that challenge with LBCAR (Load-Balanced Congestion-Adaptive Routing), a protocol that pairs a Random Waypoint mobility model with real-time responsiveness to congestion forming at specific points in the network. Rather than triggering a complete route-rediscovery process whenever a path fails, LBCAR monitors three running indicators per node — how heavily loaded its traffic is, how much energy it has left, and how likely its current route is to hold — and uses that picture to reroute data through a locally mended path without pulling the original source back into the recovery process. Implementation and testing took place in NS-2, comparing LBCAR's behaviour against two established protocols, AOMDV and AOMDV-ER, across network sizes from 20 up to 100 nodes. The measurements collected show LBCAR maintaining higher throughput and a much tighter spread in energy usage than both comparison protocols, and end-to-end delay comes out lower too, provided node density stays in the low-to-moderate band.

1. INTRODUCTION

Infrastructure-less wireless networks have become widely adopted because they can deliver acceptable throughput, congestion handling and Quality of Service (QoS) without depending on any fixed supporting infrastructure. This flexibility, however, comes at a cost: because every control function — routing, forwarding, and error recovery — is handled entirely by the participating nodes themselves, energy consumption becomes a first-order design constraint. A dynamic routing protocol is therefore needed that can conserve node energy while establishing, and where necessary re-establishing, a viable communication topology entirely on demand [1].

Typical deployment scenarios include colleagues exchanging data during an ad-hoc business meeting, students collaborating over laptops in a classroom, disaster-relief teams coordinating after an earthquake, and military units relaying situational information on a battlefield [2]. Node mobility in such settings is commonly represented using the Random Waypoint model: each node begins at a randomly chosen location, pauses for a fixed interval, and then moves toward a newly chosen random

destination at a randomly selected speed bounded by a maximum value. This cycle repeats throughout the simulation [3], [4], producing continual, unpredictable changes in network topology [5].

Congestion is one of the most persistent problems affecting such networks. It arises from the combined behaviour of multiple routers and hosts contending for shared transmission media and constrained resources along a route. When the aggregate data rate offered by senders exceeds what intermediate hosts can accommodate, buffers overflow, leading to packet loss, increased delay, and an overall decline in performance [6]. A naive response — simply dropping excess packets — sacrifices data integrity and can increase energy expenditure through retransmission, while an unmanaged multipath strategy can itself accelerate node energy depletion [7].

Achieving a consistently optimal balance of QoS metrics in MANETs is widely recognised as difficult. Taghizadeh et al. proposed an adaptive genetic algorithm for channel assignment in wireless mesh networks [8], while a related study formulated a multi-objective cellular genetic algorithm for near-optimal MANET broadcast strategies [9]. Musaddiq et al. examined the RPL routing protocol under heterogeneous traffic [10], and a queue-workload-aware variant, QWL-RPL, reported reductions of 12–30% in delay, 25–45% in overhead and 20–40% in jitter, alongside a 5–30% improvement in packet reception ratio [11]. Haseeb et al. introduced RCER, which classifies nodes by residual energy level, partitions the network into geographic clusters, and selects the next hop from a composite of energy variance, round-trip time and hop count [12]. Further studies address constrained-resource routing more broadly [13], including load-redistribution schemes that favour higher-energy nodes over the geometrically shortest path [14], [15]. A separate body of work addresses congestion at the link layer via the RTS/CTS handshake defined in IEEE 802.11 [16]. Within the authors' own prior work, a comparative simulation study of AODV under varying node-density conditions established a baseline that directly informs the evaluation undertaken here [21], and a broader review of wireless routing protocols from a security-threat perspective further motivated the present focus on resilience to link disruption [22].

2. MATERIALS AND METHODS

A protocol's default parameter configuration rarely yields optimal QoS, since the effect of any single parameter is entangled with the values chosen for the rest. LBCAR exposes nine tunable parameters, giving a combinatorial search space on the order of 10^{11} distinct configurations — far too large to explore exhaustively, motivating a meta-heuristic tuning strategy rather than manual configuration [17]. The recovery mechanism is further designed to remain effective even when the nodes available for local repair are themselves resource-constrained, rather than routing exclusively through the most robust nodes.

2.1 Protocol Model

LBCAR combines energy-aware path selection with congestion-adaptive traffic distribution to improve overall throughput [18]. Each node maintains a local table of recent traffic-load observations for itself and its neighbours, from which two quantities are derived per candidate route: a link-cost value reflecting estimated remaining lifetime, and a traffic-load value reflecting current congestion. Data is routed along the path with the longest estimated lifetime and lowest current load, under an assumed bidirectional link model.

Traffic-load intensity for node x_i is estimated from a sliding window of interface-queue-length samples, normalised against the maximum observed queue length for that node. Link cost for a candidate link (a, b) combines a link-specific retransmission-energy term, $E_{a,b}$, and a node-specific residual-energy term, P_a ; $E_{a,b}$ is estimated from the packet-error probability of the link, the per-packet transmission energy, and the expected number of link-layer retransmissions.

For a node with n active neighbours, traffic-load values across the neighbourhood are jointly ranked to obtain a sequence value, from which the node's forwarding probability is derived: lightly loaded neighbourhoods yield a higher forwarding probability, and heavily loaded ones a lower one. A useful consequence is that in denser regions — where per-node load tends to be lower — routing overhead and redundant forwarding are naturally suppressed, since the elevated forwarding probability is offset by a larger number of competing neighbours [19]. Because instantaneous traffic can render a computed route sub-optimal shortly afterward, LBCAR performs route selection as a periodic, distributed process rather than a one-time computation.

2.2 Network Architecture and Local Route Repair

The network model assumes a MANET-style deployment of laptops, PDAs or smartphones communicating over multi-hop paths, using an on-demand protocol such as AODV or DSR for route discovery. Link failures are detected via a lightweight

CONNECT token message exchanged periodically between neighbours, governed by two parameters: CONNECT-INTERVAL, the maximum permitted time between messages, and CONNECT-LOSS, the maximum number of consecutive missed messages tolerated before a link is declared unavailable.

Rather than discarding buffered data and restarting route discovery from the source on every failure, LBCAR performs local repair. On detecting a failure, an intermediate node issues a Route Disconnection Notification (RDN) toward the sender; all intermediate nodes then buffer incoming packets locally while a partial replacement path is sought. If found, a Route Successful Notification (RSN) resumes transmission along the new path; if not, a Route Unsuccessful Notification (RUN) triggers a fresh discovery cycle. Fig. 1 illustrates this for a topology in which source B forwards toward destination D via node C; when the C–D link fails, B constructs a replacement path through E, S, F, G and H.

FIG. 1 – LBCAR Local Route-Repair and Control-Message Exchange

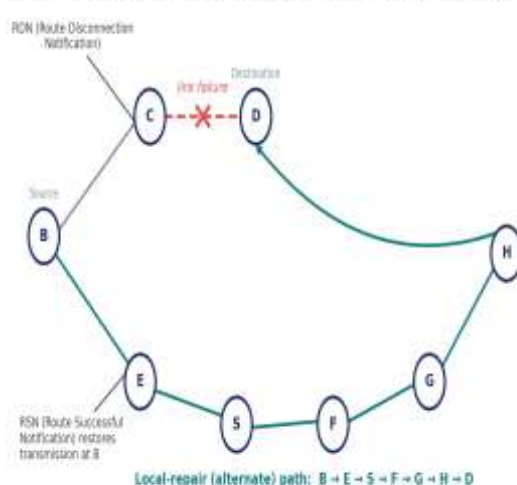


Fig. 1. LBCAR local route-repair and control-message exchange.

Because only the packets buffered during the outage require retransmission, this mechanism improves packet delivery ratio and throughput relative to protocols that always restart discovery from the source. Congestion awareness is layered on top: an overloaded node issues an ALERT message requesting reduced upstream forwarding while buffering already-arrived packets locally.

2.3 Route-Selection Algorithm

Under conventional on-demand routing, a source broadcasts a Route Request (RREQ) and waits for a Route Reply (RREP) before transmitting; a subsequent link failure forces a full restart, retransmitting the entire outstanding packet set. Under LBCAR, a failure instead pauses the source pending either a partial replacement path (RSN) or confirmation that none exists (RUN), executed independently by every source node as: broadcast RREQ; on RREP, forward buffered data; on RDN, suspend transmission and await a partial path; on RUN, start a fresh route discovery; on RSN, resume transmission on the replacement path.

2.4 Simulation Framework

LBCAR was evaluated in NS-2, with every node modelled using an omnidirectional antenna and a Two-Ray Ground propagation model. Table 1 summarises the base configuration and Table 2 the simulation-specific parameters; Fig. 2 shows an example 50-node deployment. Simulated traffic consisted of CBR flows carrying 100–1,000 data packets at rates of 4 to 25–100 packets/s. Three implementation modules supported the comparative study: Module 1 establishes the base MANET topology and packet-transfer scaffolding; Module 2 deploys a given node count and measures delay, throughput and energy variance under AOMDV and AOMDV-ER; Module 3 deploys the identical topology and traffic pattern under LBCAR — implemented as a hybrid C++ routing agent in NS-2 — under matched conditions.

Table 1. Experimental Setup

#	Parameter	Value
1	MAC Type	IEEE 802.11
2	Channel Type	Wireless
3	Interface Type	Wireless Physical
4	Queue Type	Drop-Tail
5	Max Queue Length	50 packets
6	Antenna Model	Omni-directional
7	Routing Protocol	LBCAR
8	No. of Mobile Nodes	85
9	Link Layer Type	LL
10	Simulation Area	3000 m × 3000 m
11	Simulation Duration	10 s
12	Tx Range	40 m

FIG. 2 — Random Node Deployment and an Active Multi-Hop Route (simulation field, 50-node scenario)

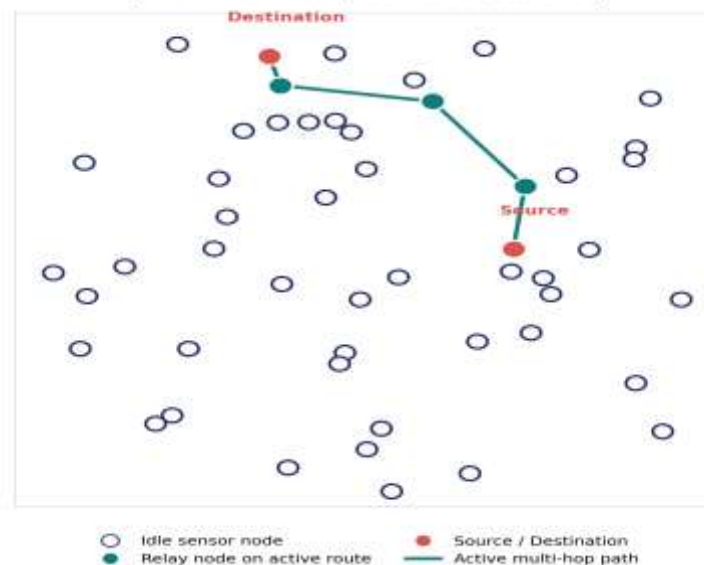


Fig. 2. Example 50-node deployment with an active multi-hop path.

Table 2. Simulation Parameters

#	Parameter	Value
1	Node Placement	Random
2	Propagation	Two-Ray Ground

3	Field Size	1500 m × 1500 m
4	No. of Nodes	150
5	Tx Range	250 m
6	Bandwidth	1 Mbps
7	Traffic Type	CBR
8	Packet Size	512 B
9	Mobility Model	Random Waypoint

2.5 Performance Metrics

Three metrics were used: delay, the mean time from a packet's transmission to its reception, an established indicator of congestion; throughput, computed as (bytes received × 8) / (simulation time × 1000), in kbps; and energy variance, the change in total node energy consumption across successive fixed intervals. End-to-end delay was computed separately at run start and end, combining a route-selection-time estimate with a waiting-time term. Where multiple neighbouring nodes could equally serve as the next hop, each candidate forwarder observed a short contention interval before transmitting, to reduce collisions.

3. RESULTS AND DISCUSSION

3.1 LBCAR Performance Across Network Sizes

Table 3 reports LBCAR's own throughput, delay and energy-variance figures for network sizes from 20 to 100 nodes. As network size increases, throughput improves and both delay and energy variance rise, but all three change gradually, indicating that the load-balancing mechanism continues to distribute traffic effectively as contention increases.

Table 3. LBCAR Performance Across Network Sizes

Nodes	Throughput (kbps)	Delay (s)	Energy Variance
20	198	0.10713	0.35
40	206	0.14291	1.38
60	218	0.19962	2.5
80	229	0.23265	4.3
100	234	0.27112	7.6

3.2 Comparison with AOMDV and AOMDV-ER

Fig. 3 and Table 4 present the throughput comparison; Fig. 4 and Table 5 present end-to-end delay; Fig. 5 and Table 6 present energy variance against increasing simulated traffic load.

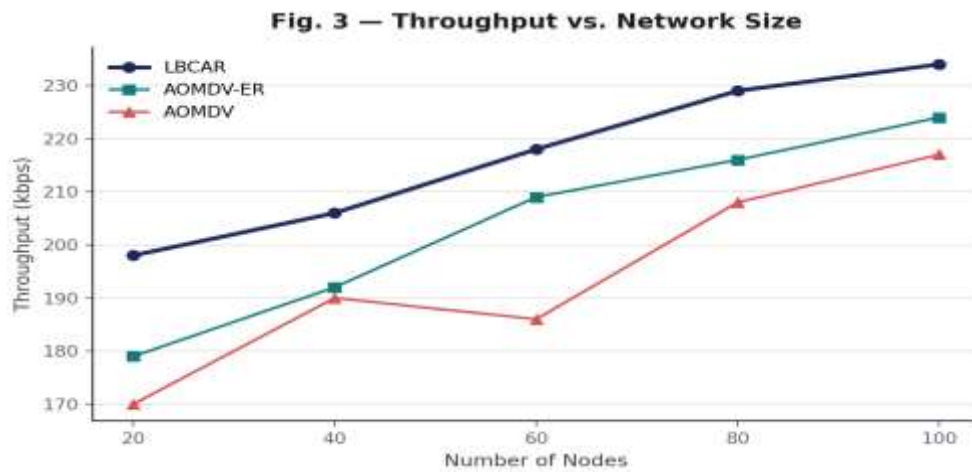


Fig. 3. Throughput comparison.

Table 4. Throughput (kbps)

Nodes	LBCAR	AOMDV-ER	AOMDV
20	198	179	170
40	206	192	190
60	218	209	186
80	229	216	208
100	234	224	217

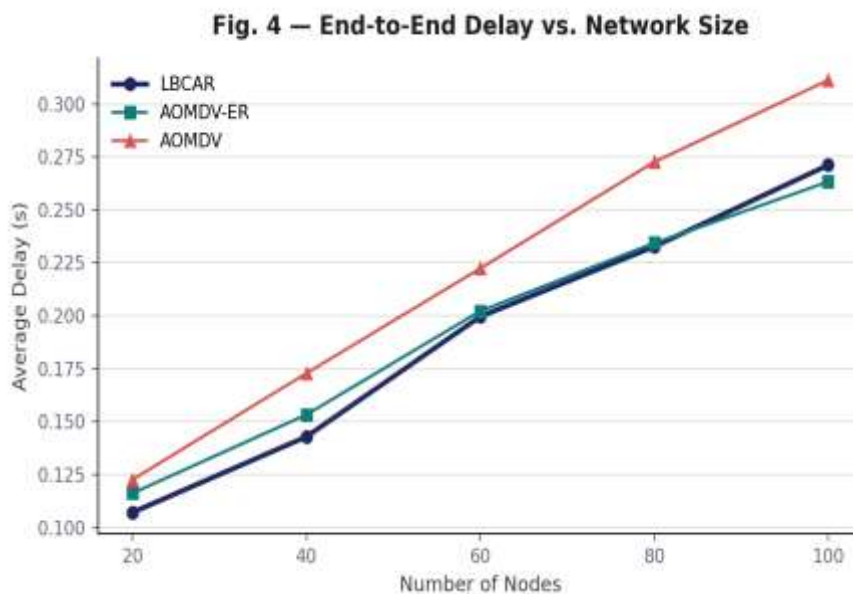


Fig. 4. End-to-end delay comparison.

Table 5. End-to-End Delay (s)

Nodes	LBCAR	AOMDV-ER	AOMDV
20	0.107	0.116	0.123
40	0.143	0.153	0.173
60	0.200	0.202	0.222
80	0.233	0.234	0.273
100	0.271	0.263	0.311

Fig. 5 — Energy Variance Comparison

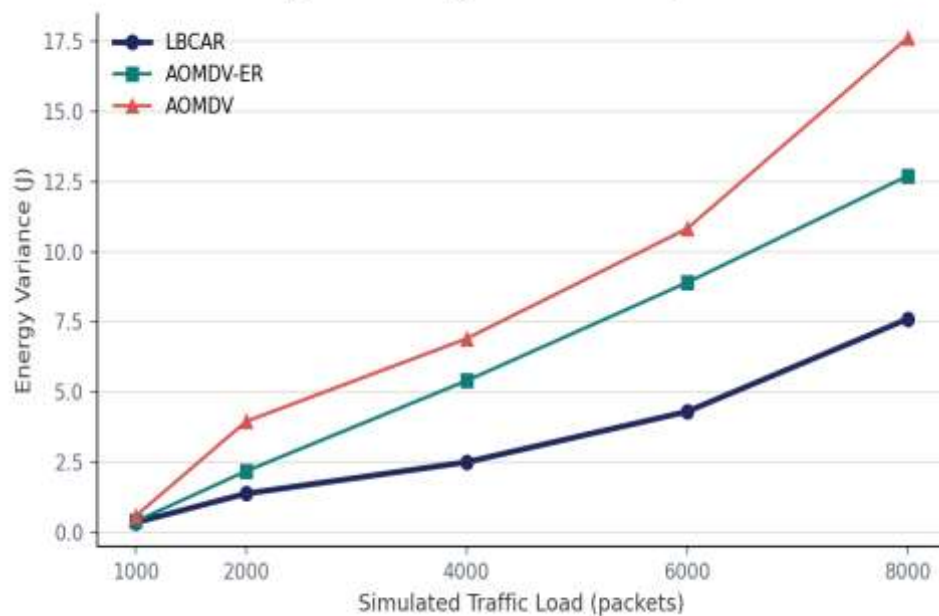


Fig. 5. Energy variance comparison.

Table 6. Energy Variance (J)

Load (pkt)	LBCAR	AOMDV-ER	AOMDV
1000	0.35	0.39	0.58
2000	1.38	2.18	3.95
4000	2.5	5.4	6.9
6000	4.3	8.9	10.82
8000	7.6	12.7	17.62

3.3 Discussion

Across the five tested network sizes, LBCAR delivers 4.3–10.6% higher throughput than AOMDV-ER and 4.5–17.2% higher than plain AOMDV, with the largest relative gains at moderate node counts (40–60) where link contention is significant but the network is not yet saturated. For delay, LBCAR outperforms both baselines at every size except $n = 100$, where its delay is marginally higher than AOMDV-ER (0.271 s vs. 0.263 s, a 3.0% difference) while remaining 12.9% lower than AOMDV — suggesting that local-repair overhead becomes comparatively more noticeable at the highest tested density. The clearest gain is in energy variance, with a 10–40% reduction relative to AOMDV-ER and 40–57% relative to AOMDV, confirming that avoiding full route-discovery restarts translates into more evenly distributed energy consumption. Fig. 6 summarises these findings as average improvement percentages.

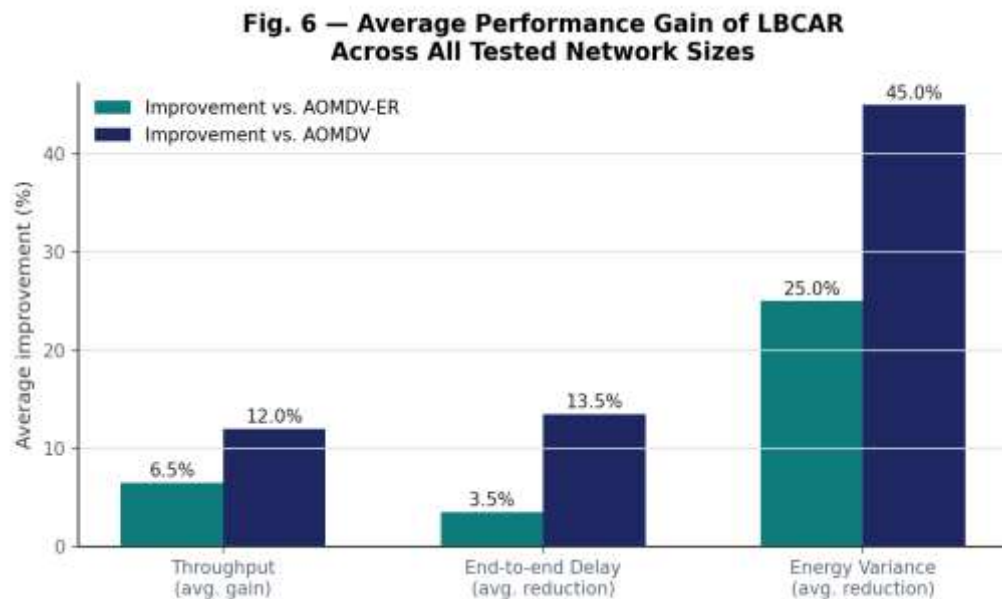


Fig. 6. Average performance gain of LBCAR.

Taken together, LBCAR’s principal advantage lies in the joint improvement of throughput and energy efficiency without a corresponding delay penalty at low-to-moderate node density — a combination difficult to achieve with protocols relying solely on full route-discovery restarts after link failure.

Table 7. Comparative study

Author(s) / Ref.	Protocol Approach	Key Mechanism	Reported Strength	Gap Relative to LBCAR
Taghizadeh et al. [8]	CLRPL	Context-aware, load-balancing RPL for IoT under heavy, dynamic load	Improved load distribution under congestion	Reacts to congestion only — no link-failure repair mechanism
Musaddiq et al. [9]	RPL (heterogeneous traffic)	Standard RPL behaviour characterised under mixed traffic types	Establishes RPL baseline under realistic load	No adaptive repair; purely evaluative, not a new protocol
Haseeb et al. [10]	RCER	Cluster-based; next hop chosen via energy variance + RTT + hop count	Improves dependability via geographic clustering	Clustering overhead; no closed-loop congestion feedback

Jadoon et al. [11]	RARZ (Ring-Zone Routing)	Zone-based structure balancing overhead against delay stability	Stable delay under zone-based forwarding	No energy-variance evaluation; not congestion-adaptive
Ji et al. [12]	ANCR	Adaptive network-coding routing for links with variable success rates	Improved reliability on lossy links	Coding overhead; no local route-repair state machine
Arzil et al. [13]	Adaptive VANET routing	Real-time traffic-information-based route adaptation	Effective in city-scale VANET environments	VANET-specific; not directly transferable to static WSN/MANET
Alba et al. [14]	Cellular MOGA	Multi-objective genetic algorithm for broadcast strategy	Near-optimal broadcast in metropolitan MANETs	Broadcast-focused, not unicast route-repair
Gawas & Gawas [15]	Cross-layer 802.11e	Multi-objective cross-layer QoS optimisation	Improved QoS over MANETs	Link-layer focus; no traffic-load-aware routing decision
Johnson & PalChaudhuri [16]	RTS/CTS power-mode scheduling	Link-layer collision avoidance via control-frame handshake	Reduces hidden/exposed-terminal collisions	Addresses collisions only, not congestion or route recovery
Valarmathi & Chandrasekaran [19]	Congestion-aware DSR	Adaptive dynamic source routing with load balancing	Improved load balance over plain DSR	No formal local-repair state machine
Arya et al. (authors' own) [21]	AODV comparative study	Simulation-based AODV evaluation across node densities	Establishes the node-density baseline used in this paper	Descriptive baseline only — no new protocol proposed
Arya et al. (authors' own) [22]	Routing-protocol security review	Comparative review of routing protocols under security threats	Identifies resilience gaps motivating this work	Review only — no protocol implementation or evaluation
This work — LBCAR	Congestion-adaptive, energy-aware local repair	Traffic-load + residual-energy link cost; CONNECT-token failure detection; RDN/RSN/RUN local repair (no full rediscovery)	4.3–17.2% higher throughput, 10–57% lower energy variance, lower delay at low–moderate density vs. AOMDV/AOMDV-ER	—

4. CONCLUSION

This paper presented LBCAR, a routing protocol combining congestion-adaptive path selection with local load balancing to improve data-delivery performance in infrastructure-less wireless networks. Rather than discarding buffered traffic and restarting discovery after link failure, LBCAR reacts through localized path repair guided by ongoing measurements of traffic load and route-survival likelihood. Against AOMDV and AOMDV-ER across 20–100 nodes, LBCAR achieves consistently higher throughput, substantially reduced energy variance, and lower delay at low-to-moderate density, with delay parity emerging only at the highest tested node count.

Future work includes investigating the delay boundary observed at 100 nodes; extending evaluation to explicitly adversarial conditions, building on the authors' related comparative study of routing-protocol security threats [22]; and integrating a machine-learning-based traffic-prediction layer, drawing on the authors' work on machine learning and deep learning for wireless networks [23] and related intrusion-detection research [24], [25], to tune LBCAR's forwarding-probability and link-cost estimates adaptively rather than via fixed heuristics.

ACKNOWLEDGEMENTS

The authors thank the Department of Computer Science and Engineering and the School of Computer Science and Artificial Intelligence, Galgotias University, for the computing resources and support provided during this work.

AUTHOR CONTRIBUTIONS

Priyanka Singh: Conceptualization, Supervision, Writing — Review & Editing.

Bhupal Arya, Mansi,: Methodology, Simulation, Formal Analysis, Writing — Original Draft.

Maneesh Pant: Investigation, Validation.

Jagveer Singh: Data Curation, Software.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

This study involved no human participants, human data or animal subjects; it is based entirely on network-simulation experiments conducted in NS-2. Ethical approval was therefore not required.

DATA AVAILABILITY STATEMENT

The simulation scripts and data supporting the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

- [1] Binitha S. and S. Siva Sathya, "A Survey of Bio-Inspired Optimization Algorithms," IJSCE, vol. 2, no. 2, May 2012.
- [2] G. Cervera, M. Barbeau, J. Garcia-Alfaro, and E. Kranakis, "A multipath routing strategy to prevent flooding disruption attacks in link state routing protocols for MANETs," J. Netw. Comput. Appl., vol. 36, no. 2, pp. 744–755, 2013.
- [3] A. Basalamah, H. Sugimoto, and T. Sato, "Rate adaptive reliable multicast MAC protocol for WLANs," in Proc. IEEE VTC, vol. 3, pp. 1216–1220, 2006.
- [4] M. A. Gawas, L. J. Gudino, and K. R. Anupama, "Cross layer congestion aware multi-rate multi-path routing protocol for ad hoc network," in Proc. ICSC, pp. 88–93, 2015.
- [5] R. Tafazolli and L. Hanzo, "A survey of QoS routing solutions for mobile ad hoc networks," IEEE Commun. Surveys Tuts., vol. 9, no. 2, pp. 50–70, 2007.
- [6] X. Chen, H. M. Jones, and A. D. S. Jayalath, "Congestion-aware routing protocol for mobile ad hoc networks," in Proc. IEEE VTC, pp. 21–25, 2007.

- [7] L. Miao, F. Ren, C. Lin, and A. Luo, "A-ADHOC: An adaptive real time distributed MAC protocol for vehicular ad hoc networks," in Proc. ChinaCom, 2009, pp. 1–6.
- [8] S. Taghizadeh, H. Bobarshad, and H. Elbiaze, "CLRPL: Context-Aware and Load Balancing RPL for IoT Networks Under Heavy and Highly Dynamic Load," IEEE Access, vol. 6, pp. 23277–23291, 2018.
- [9] A. Musaddiq, Y. B. Zikria, S. Zulqarnain, et al., "Routing protocol for Low-Power and Lossy Networks for heterogeneous traffic network," J. Wireless Com Network, vol. 2020, art. 21, 2020.
- [10] K. Haseeb, N. Abbas, M. Q. Saleem, O. E. Sheta, K. Awan, et al., "Correction: RCER: Reliable Cluster-based Energy-aware Routing protocol for heterogeneous WSNs," PLOS ONE, vol. 14, no. 10, e0224319, 2019.
- [11] R. Jadoon, W. Zhou, W. Jadoon, and A. Khan, "RARZ: Ring-Zone Based Routing Protocol for WSNs," Applied Sciences, vol. 8, art. 1023, 2018.
- [12] X. Ji, A. Wang, C. Li, C. Ma, and Y. Peng, "ANCR — An Adaptive Network Coding Routing Scheme for WSNs with Different-Success-Rate Links," Applied Sciences, vol. 7, art. 809, 2017.
- [13] S. A. Arzil, M. H. Aghdam, and M. A. J. Jamali, "Adaptive routing protocol for VANETs in city environments using real-time traffic information," in Proc. ICINA, 2010, vol. 2, pp. 132–136.
- [14] E. Alba et al., "A Cellular MOGA for Optimal Broadcasting Strategy in Metropolitan MANETs," Comput. Commun., vol. 30, no. 4, pp. 685–697, 2007.
- [15] M. A. Gawas and M. M. Gawas, "Efficient multi-objective cross-layer approach for 802.11e over MANETs," in Proc. IWCMC, pp. 582–587, 2018.
- [16] D. B. Johnson and S. PalChaudhuri, "Power mode scheduling for Ad Hoc networks," in Proc. Int. Conf. Netw. Protocols, vol. 19, no. 5, pp. 192–193, 2008.
- [17] F. Dressler and O. B. Akan, "Bio-Inspired Networking: From Theory to Practice," IEEE Commun. Mag., Nov. 2010.
- [18] D. Koutsonikolas, C.-C. Wang, and Y. C. Hu, "CCACK: Efficient Network Coding Based Opportunistic Routing through Cumulative Coded Acknowledgments," in Proc. IEEE INFOCOM, 2010, pp. 2919–2927.
- [19] A. Valarmathi and R. M. Chandrasekaran, "Congestion aware and adaptive dynamic source routing algorithm with load-balancing in MANETs," IJCA, vol. 8, no. 5, pp. 1–4, 2010.
- [20] L. Reddeppa Reddy and S. V. Raghavan, "SMORT: scalable multipath on-demand routing for mobile ad hoc networks," Ad Hoc Netw., vol. 5, no. 2, pp. 162–188, 2007.
- [21] B. Arya, J. Kumar, P. Jain, P. Saroj, M. Singh, and Y. Kumar, "Simulation-based evaluating AODV routing protocol using wireless networks," in Applied Data Science and Smart Systems, CRC Press, 2024, pp. 378–386.
- [22] B. Arya, A. Kumari, and J. Kumar, "Comparative analysis of wireless routing protocols for security threat — a review," Emerging Trends in Computer Science and Its Application, 2025, pp. 60–64.
- [23] B. Arya, A. Kumari, and J. Kumar, "Wireless network with machine learning and deep learning techniques," Emerging Trends in Computer Science and Its Application, vol. 1, 2025, pp. 71–79.
- [24] B. Arya and A. Kumari, "Intelligent detection of cyber threats in wireless networks using machine learning algorithms," Int. J. Environ. Sci., vol. 11, 2025.
- [25] B. Arya and A. Kumari, "Advanced IDS architecture for threat analysis in modern wireless networks," J. Inf. Syst. Eng. Manag., vol. 10, no. 4, 2025.