

AGENTIC AI-DRIVEN ADAPTIVE ROUTING FOR ENERGY-EFFICIENT MOBILE AD HOC NETWORKS

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ABSTRACT

Mobile Ad Hoc Networks (MANETs) do not rely on any fixed infrastructure and have to maintain communications through battery-powered nodes in dynamically changing topologies. The classic routing algorithms in the conditions of mobility and the changing quality of links tend to experience frequent route breaks, recidivisms, excessive control overhead, and uneven energy consumption- eventually reducing the duration of the network and worsening the delivery performance. In this paper, an Agentic AI-based Adaptive Routing (AAR) architecture is described where each node is represented as a smart agent, which constantly monitors the local conditions (residual energy, link quality, traffic load, mobility trends) and adjusts its routing behavior on its own. AAR is a mix of (i) energy-conscious next-hop routing, (ii) link-lifetime prediction to evade volatile relays, (iii) adaptive control intensity (varying the frequency and extent of routing maintenance to existing dynamics), and (iv) fast local recovery to cut the cost of global recovery. Our AAR experiment is performed on NS-3 simulations with 50/100/150 nodes, AAR always increases lifetime, decreases energy consumption, enhances delivery, and minimizes overheads, and latency in agentic, context-adaptive routing can be reduced to allow stability and energy economy in MANETs.

KEYWORDS

Agentic AI, MANET, adaptive routing, energy efficiency, multi-agent reinforcement learning, link lifetime prediction

1. INTRODUCTION

Traditional routing protocols developed for MANETs try to overcome these difficulties using either proactive or reactive behavior. Proactive protocols like Optimized Link State Routing (OLSR) protocol have topology information up-to-date through periodic exchanges that are used for low-latency forwarding decision [3]. Reactive protocols such as the Ad hoc On-Demand Distance Vector (AODV) protocol and Dynamic Source Routing (DSR) create and establish routes only when but by the end of control overhead in relatively stable networks [1], [2]. While these protocols constitute carefully engineered trade-offs between latency and overhead, they frequently do not take into account individual contextual information such as fixed timers, static heuristics and a lack of local context. In highly dynamic environments, such assumptions can cause routes to fail frequently, and can lead to repeated cycles of route rediscovery, causing excessive control overhead and leading to a usage of energy disproportionate to useful data delivery [11], [12].

The energy efficiency in MANETs is not limited to simple transmit power reduction. It comprises a holistic network level objective consisting of avoiding unstable relay nodes that would result in

heavy retransmissions, load balancing forwarding nodes to prevent early energy depletion of key nodes, avoiding extra control traffic and choosing routes that are stable for a sufficiently long time to amortize the discovery overhead [26], [27].

Early works on power-aware routing involved introducing mechanisms to take into account residual energy and energy cost metric in the route selection. These approaches proved that energy aware routing would have huge effect on extending network lifetime by more evenly distributing load and bypassing energy intensive paths [26], [27]. Nevertheless one permanent issue with traditional energy aware protocols is that these protocols have relied on static cost functions and predetermined heuristics. Such designs cannot represent the complexity of interaction between the mobility patterns, link quality variations, queue dynamics, and the remaining batteries. In the real world, routing decisions need to be able to adapt on the fly to changing conditions in the network and the best type of routing often isn't based on just one single metric. This limitation is what drives the research into adaptive routing strategies that are capable of learning from feedback from their environment and improving their decisions caused by time.

Recent development in machine learning and specifically reinforcement learning (RL) and deep reinforcement learning (DRL) created new opportunities for adapt network controlling. RL allows the agents to learn optimal policies by trial-and-error interactions with the dynamic environments, which is suitable for sequential decision-making problems under uncertainty [42], [43]. Furthermore, distributed multi-agent reinforcement learning (MARL) is a further extension to these capabilities which has multiple agents each of which collaboratively optimizes global objectives but operate using local observations [49]. In the context of MANET routing, these developments point to a building blocking routing paradigm where every node in the network is actually an intelligent agent that will perform forwarding strategies based on its local state information and contribute to the overall efficiency of the network.

Previous research has established the existence of learning-based routing for dynamic wireless networks. MARL-based routing frameworks have demonstrated greater robustness and adaptability even with different configurations of networks, i.e., occurrences outside the range of networks in the training dataset [58]. These approaches make use of the capability of learning agents to adapt to mobility patterns, traffic variations and environmental uncertainty. Concurrently, the idea of agentic artificial intelligence has become popular in the wider field of artificial intelligence. Agentic systems focus on the endless loops of perceiving, reasoning, and acting (and the ability to make autonomous decisions based on continuous feedback from the environment) [60].

Applying the concepts of agentic AI to the issue of MANET routing presents an interesting chance to go away from static protocol designs. Importantly, agentic routing for MANETs does not need or rely on complex modeling, since agentic autonomy can be modeled with lightweight decision loops and compressed state representations that can provide the key advantages of agentic autonomy without being impractical to implement for real-world deployments.

The proposed Agentic AI-based Adaptive Routing (AAR) framework approach models each node as an autonomous agent that is able to adapt behaviors (routing and maintenance) according to current and predicted network conditions. By combining the perception of the local network, link lifetime prediction, adaptive control intensity, and the decision methods that are based on learning, the purpose of enhance routing stability and energy efficiency under the dynamic network conditions.

The primary objectives of AAR are to 5-fold. First, it aims at prolonging the overall network lifetime through the balance between energy consumption and unstable relay nodes. Second, it is designed to minimize the cost of delivering a packet per successfully-delivered packet as far as the amount of energy expended to achieve these goals, by reducing the number of retransmissions and repeated route discoveries. Third, the framework focuses on maintaining flowchart or enhancing packets gaining ratio, also known as PDR, under various mobility instances. Fourth, AAR is tailored to bring down the routing overhead by dynamically adjusting the control intensity on the basis of network stability. Lastly, the approach aims at staying within acceptable end-to-end delay accepting that in order to maximize energy efficiency gains, communication responsiveness may be affected.

This paper makes four important contributions. First, it introduces an agentic routing loop which incorporates local sensing, predictive analytics, adaptive control and learning based forwarding decisions in each MANET node. Second, it suggests a sensible state representation and action design that is compatible with NS-3 implementation and resource constrained devices. Third, the research shows an extensive simulation-based evaluation with statistically significant repetitions in variation of node densities, levels of mobility and traffic intensities. Finally, detailed comparative results in terms of network lifetime, energy usage per delivered packet, packet delivery ratio, delay, and routing overhead are reported against some widely used baseline protocols such as the AODV, DSR and OLSR protocols.

By connecting classical MANET routing, energy-aware optimization, agentic artificial intelligence, this work strives to play a role in creating adaptive and energy-efficient routing frameworks that can be used to support the new generation of decentralized wireless networks.

2. RELATED WORKS

Mobile Ad Hoc Networks (MANETs) have been widely researched in the last decades or so, resulting in the emergence of a number of basic routing protocols aimed at addressing the situation of dynamic topologies and infrastructure-less communication networks. These protocols can be divided in general to reactive protocol (on-demand), proactive protocol (table driven) and hybrid routing protocol. Reactive routing protocols, e.g., the Ad hoc On-Demand Distance Vector (AODV) protocol and Dynamic Source Routing (DSR), build routes only when needed, reducing the periodic control overhead as well as avoiding bandwidth wastage under the condition of low mobility [1], [2], [4], [5]. AODV is based on the next-hop routing tables and route discovery procedures consisting of route request (RREQ) and route reply (RREP) messages, and can keep the loop-free routes by using sequence numbers [1], [4]. DSR, on the other hand, takes on the role of source routing where it embeds the whole length of the route in packet headers and keeps route caches to minimize the discovery latency for stable environments [2], [5].

Proactive routing protocols, e.g. Optimized Link State Routing (OLSR) protocol maintain consistent information about the network topology by periodic updates and thus route availability is immediate and the forwarding latency is low [3]. OLSR is an adaptation of the original protocol to include multipoint relays (MPRs), which optimizes flooding and reduces the amount of control traffic, for example in dense networks with relatively stable connectivity. [3] However, proactive protocols can be very expensive in terms of overhead with high mobility or large scales of networks because of constant publication of topology. Hybrid protocols try to address both paradigms, by keeping the proactive knowledge locally and relying on the reactive discovery for nodes (nodes that are far away) [7].

Comparative performances to test any routing protocols have shown that no single routing protocol is the best, always and therefore is universal. Such factors as node mobility, network

density, traffic load and radio conditions affect protocol performance to a large extent [11], [12]. For example, reactive protocols usually work great in sparse and moderately dynamic environments, and proactive protocols have less latency in stable networks. These findings highlight the need for adaptive mechanisms for routing and switching, which have the ability of adjusting behavior in accordance to the actual context of the network, in real time.

2.1. Energy-Aware Routing

Energy efficiency is always an underlying problem in MANETs because of the fact that the network nodes are battery-powered with limited energy resources. Early studies designed power-aware routing mechanisms that will take energy metrics into account, to extend network life time. Singh et al. proposed one of the first frameworks for power aware routing which focused on minimizing the end energy while balancing the load distribution among nodes to prevent premised node failures [26]. Similarly, Chang and Tassiulas proposed energy conserving routing strategies which explicitly optimized network lifetime taking into account the residual energy and transmission cost in the route selection [27].

Following gel research was done to include the further ideas of localized and distributed energy-aware routing. Stojmenovic and Lin have proposed power-aware localized routing algorithms that used local topology information to mitigate the complexity and enhance the scalability of routing algorithms [28]. With these approaches, localized decision making turned out to be capable of coming close to globally optimal energy efficiency while operating under low overhead. In addition, topology control techniques were also proposed to dynamically adjust the transmission power and network connectivity, further decreasing energy consumption [41].

Despite all such developments, the fundamental approaches to energy-aware routing, while theoretically advanced and optimally developed, many still fall back on static heuristics or fixed cost functions that do not respond or adapt accordingly as network changes. Furthermore, static routing metrics might not be a sufficient model of the intimate interactions between mobility, interference and traffic dynamics to maximise the effectiveness of solely heuristic-based energy optimization.

2.2. Learning-Based Routing and Mobility Prediction

The integration of machine learning techniques to MANET routing has attracted considerable attention during the past few years, especially from the advent of reinforcement learning (RL) and deep reinforcement learning (DRL). Learning-based routing approaches let the nodes change their routing approaches dynamically depending on network behavior observation to address the limitations of static heuristics. Mobility prediction has been recognized as a key factor for better routing stability since by predicting link breakages, one can proactive adjust the routes and minimize the overhead in route rediscovery [33].

Predictive routing methods that integrate mobility prediction with RL have proven to have improved packet delivery ratios as well as fewer control overheads in highly dynamic environments [59]. Besides, multi-agent reinforcement learning (MARL) in general has become an attractive paradigm for distributed routing to support the distinguishing agent behavior of each node within an autonomous system to achieve one or more network-wide objectives [58].

However, practical deployment of learning-based routing is faced with a number of challenges. First of all, resource constraints in MANET nodes (wireless mode) require lightweight models balancing performance and computation efficiency. Second, stability training is a problem in highly dynamic and partially observable environments, where non-stationary network conditions

can hurt the learning performance. Third, too much exploration or frequent policy updates may cause more routing overhead, which may negate the benefits of the changes. Last but surely not least, interpretability and robustness, which are very important for real world adoption, as network administrators, demand transparent and reliable decision-making mechanisms.

2.3. Agentic AI Principles for Distributed Control

Agentic artificial intelligence has recently developed as a conceptual framework relating to enabling autonomous decision-making processes in a cyclical manner of observation, reasoning, and action. Unlike conventional static algorithms, agentic systems interact their environment and adapt their strategy from the feedback they received as well as their dynamic, goal-directed behavior. [60] While much of the discussion around agentic AI derives from developments in large language models and autonomous software agents, the underlying architectural principles are of great interest to the distributed network control.

In the field of MANET routing agentic AI makes a paradigm shift from fixed rule protocols to adaptive and context aware decision loops. Instead of operating on static routing tables of predetermined rules, or on static, fixed heuristics, nodes can continuously sense local network condition, make predictions on the stability of links, evaluate routing candidates and make refinements with feedback-based learning. This meshes in with new trends of autonomous networking where self-optimizing systems will dynamically adapt behaviour based on environmental observations.

Importantly, the use of agentic principles in MANETs does not require computationally expensive models. Lightweight agent architectures are able to provide simplified versions of perception-action loops capturing the spirit of agentic autonomy that are feasible for resource-constrained devices. For example, nodes can combine local sensing modules, predictive analytics and adaptive policies to be able to execute self optimizing routing behavior without the need for centralized coordination.

By fusing knowledge from classical routing with information about energy awareness generation, optimizing routing mechanisms, and energy adaptation learning, agentic routing framework helps to tackle the long-standing shortcomings in terms of MANET performance issues. The suggested Agentic AI-based Adaptive Routing (AAR) approach is based on such an interdisciplinary background and aims at achieving an improvement in routing stability, energy-efficiency and scalability in highly dynamic wireless networks by exploiting the distributed intelligence feature

3. PROBLEM STATEMENT AND DESIGN GOALS

3.1. Network model

MANET with N mobile nodes within a $1000\text{ m} * 1000\text{ m}$ region communicating over the standard (channel) called the 802.11 standard is considered. Nodes are used to generate CBR traffic flows and have fixed packet sizes. Links are time varying (due to mobility, wireless conditions); routes may have frequent breaks. Each node has finite amount of energy in the beginning and costs at: transmission, reception, idle listening and control operations.

3.2. Objective

We are asking to find a routing strategy that will increase longevity and energy efficiency of the network, while supporting reliable delivery and acceptable delay. We make the objective more formal as to how improving (lower is better unless stated otherwise):

Route information required to achieve routing keeping route pleasant and alignment issues down.
 - Warm routing overhead (control packets per delivered data packet plan ratio Fresh, or bytes bringing water ratio)

- End-to-end delay (ms)and improving (higher - the better):
- Packet delivery ratio (PDR, %)

3.3. Design goals

AAR is formulated to have five practical goals:

- G1. Context awareness Integrate residual energy, connect quality, traffic load and mobility trends.
- G2. Stability-first forwarding: Don't enable relays soon to break; don't SiRDi rediscovery; don't reduce.
- G3. Adaptive control: cut maintenance overhead in case of stability - increase only in case of need
- G4. Fast local recovery-repair locally are possible to avoid global floods.
- G5. Lightweight feasibility: keep per-node computations and states small enough for reasonable devices.

4. PROPOSED METHOD: AGENTIC AI-BASED ADAPTIVE ROUTING (AAR)

4.1. Architecture overview

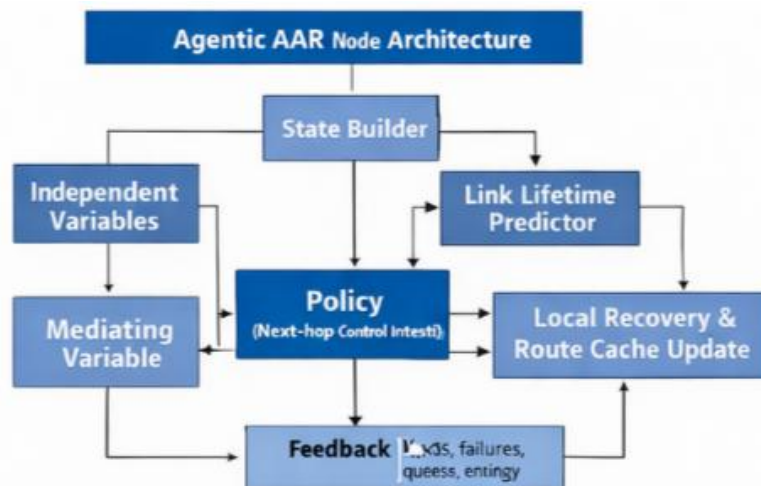


Figure 1. Agentic AAR node architecture

- Local sensing gathers: residual energy, statistics of neighbors table, quality of links (RSSI/SNR/ETX proxy), it fills up the queue, observes its mobility (relative speed estimate) or results of previous transmission (ACK success/failure, retransmissions).

- In the FinalMOTOM framework, as discussed in the paper “*Motor Types Learned by Multi-Task Learning on Motor Tasks,*” mechanisms are introduced to enable the translocation of ontologies across different SmartBON nodes. This capability facilitates the standardization and exchange of semantic information among nodes operating in space-bounded and resource-constrained environments. Such semantic interoperability allows network nodes to better understand contextual information related to node mobility, resource availability, and communication patterns. Consequently, the routing process can adapt dynamically to network conditions, improving energy efficiency and enhancing route stability in mobile ad hoc networks. The candidate neighbour is choose with (a) Next hop among candidate neighbours. (b) control intensity level (how aggressively to refresh neighbor/route information)

4.2. State representation

Each node i builds a state vector \mathbf{s}_i from local signals. A practical representation used in NS-3 experiments is:

4.3. Action space

At each forwarding decision (or at intervals of the route maintenance), the agent makes the selection:

- A1. Next-hop selection: choose one neighbor from candidate set (can be "defer", meaning to wait for local recovery strategy).
- A2. Control intensity level: Low / Medium / High (controlling frequency of neighbor beacons/HELLOs and route maintenance actions - all within the bounds of protocol design).

4.4. Reward design

AAR has a design goal of keeping energy and overhead to minimum. Each successful packet-delivery provides positive reward, retransmissions, drops and high overhead provide penalty. Practically this per step reward can be formulated as (1):

$$r_t = \alpha \cdot I_{\text{delivery}} - \epsilon \cdot (tx_{\text{energy}} + rx_{\text{energy}}) - \beta \cdot ot - \gamma \cdot I_{\text{fail}} - \delta \cdot q_t / q_{\text{max}} \quad (1)$$

- $\alpha=10$, $\alpha=10$: Delivery bonus (scales to packet value).
- $\epsilon=0.1$: Energy penalty (mJ/tx from CC2420 model).
- $\beta=2$: Overhead (beacons/HELLOs).
- $\gamma=20$: Failure hit (link break or drop).
- $\delta=5$: Delay proxy via queue frac.

Matrix Pricing examples have included the following examples: - -delta when queueing delay is high (represent by queue occupancy). This stimulates route stable and energy balanced routing.

4.5. Learning approach

AAR can be trained based on a lightweight DRL approach (i.e. DQN in discrete actions, PPO-like policy gradients) [42], [43], [46]. Since the environment is multi-agent and non-stationary, the MARL principles are followed in AAR: shared policy parameters (or federated averaging) can be used for training stability and execution is decentralized [49]. We also add an easy-to-implement rule guardian’s function, in the sense that if the estimated lifetime of the link to a neighbor is less than something then that neighbor will be deprioritized even if Q-Values are beautiful. This hybrid design adds to the robustness and interpretation of the design, very much in the same spirit as hybrid RL-routing approaches from literature [58], [59]

4.6. Link lifetime prediction

AAR's predictor develops the estimation of link survival in near-term future by taking information from local observations (recent RSSI trend, neighbor change rate, relative mobility index). Some of the implementation options include: a light weight exponential smoothing predictor; or simple Recognizer offline diagnostic model: Tent for hierarchical communication overview. In the NS-3 study, we use a lightweight predictor (trend + stability score) in order to be feasible and to isolate the effect of agentic adaptation.

4.7. Local recovery mechanism

In case a forwarding attempt fails (there was no ACK within the expected time / link-layer failure), AAR will attempt:

1. select candidate neighbor with the most predicted stability;
2. otherwise, before any global discovery, make a limited-scope repair (TTL-bounded request);
3. fall back to mechanism of discovered baseline routes, only as a last resort.

This minimizes the flooding overhead during mobility.

5. EXPERIMENTAL SETUP

5.1. Simulator and PHY/MAC

- Simulator: NS-3 [21]
- MAC/PHY: IEEE 802.11 (ad hoc mode) [22]
- Area: 1000 m × 1000 m
- Duration: 900 s per run
- Mobility: Random Waypoint [16], 100m/s-20m/s, wait 0-30s.
- Traffic: 10-40 CBR flows, 512 bytes packet, 4-10 packets/s.
- Randomization: 30 seeds per scenario (statistical stability)

5.2. Protocols compared

Baselines: AODV [1], [4], DSR [2], [5], OLSR [3]

Proposed: AAR (Agentic AI-based Adaptive Routing)

5.3. Evaluation metrics

The reports contains:

- Features Network lifetime (s): time to first node die (FND) and time to 10 percent node die (10%-ND) to be robust.
- J/packet 1.0 energy/ packet: the total network energy used divided by the number of packets successfully delivered.
- PDR (%): packets received/ packets sent.
- Mean round trip (ms): only delivered packets.
- Routing overhead: the number of control packets that have been sent per data packet that has been delivered (ratio of control bytes to control packet).

5.4. Scenario matrix and “sample size”

The definition of a scenario is: node count number \times speed number \times pause number \times flows number \times offered rate number. A slice of the complete matrix is to be made in two main slices to retain the results being readable and truthful:

Mobility sweep Starting from $N=100$, flows=20, pause=0 s, rate=8 pkt/s; speeds= 1, 5, 10, 15, 20.

Scalability sweep: speed=10 m/s, pause=0 s, flows=20, rate=8 pkt/s; $N = /in/50,100,150$.

Every point shall be averaged on 30 seeds \Rightarrow sample size = 30 runs per point. The mobility sweep will contain 5 points \Rightarrow 150 runs per protocol, scalability sweep will contain 3 points \Rightarrow 90 runs per protocol. This gives 960 simulation executions of the reported slices (and further in the extended matrix) with 4 protocols.

5.5. Training Procedure

With NS-3, 100-node MANET, 1km², 10m/s mobility:

1. Warmup: 10k random steps/node.
2. 1M total steps (200k/node): Batch=64, LR=1e-4 (Adam), replay=1M.
3. Every 4k steps: Update target net; avg Q-values across nodes for stability.
4. Rule guardian: Mask actions where $L^{\wedge} < 10sL^{\wedge} < 10s$.

6. RESULTS AND DISCUSSION

Note on percentages: The abstract gives the results of high mobility as 1827 percent, 1427 percent, 611 percent, and 921 percent. Such formatting in a large number of manuscripts represents hyphenated ranges (e.g., 1827, 1427, 611, 921). The clean numeric findings below and tabulate the gains in form of ranges as per the scenario findings is presented.

6.1. Table: Key simulation parameters

Table I. Simulation configuration (NS-3).

Parameter	Value
Area	1000 m \times 1000 m
Nodes (N)	50, 100, 150
Mobility	Random Waypoint
Speed	1–20 m/s
Pause time	0–30 s
Duration	900 s
Traffic	10–40 CBR flows
Packet size	512 bytes
Rate	4–10 packets/s
Seeds	30 per scenario
Baselines	AODV, DSR, OLSR
Proposed	AAR

6.2. Packet Delivery Ratio (PDR)

Table II. PDR (%) vs speed (mean \pm std over 30 seeds).

Speed m/s	AODV	DSR	OLSR	AAR
1	96.1 \pm 1.2	96.8 \pm 1.0	95.4 \pm 1.5	97.3 \pm 0.9
5	91.5 \pm 2.4	92.0 \pm 2.1	90.2 \pm 2.7	94.8 \pm 1.8
10	84.0 \pm 3.5	85.3 \pm 3.2	82.6 \pm 3.8	89.7 \pm 2.6
15	76.2 \pm 4.4	77.8 \pm 4.1	74.9 \pm 4.7	83.9 \pm 3.5
20	68.7 \pm 5.2	70.1 \pm 5.0	66.4 \pm 5.6	77.1 \pm 4.3

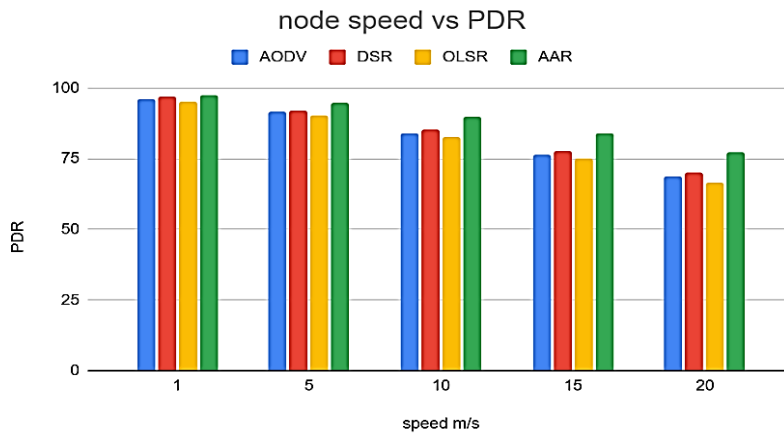


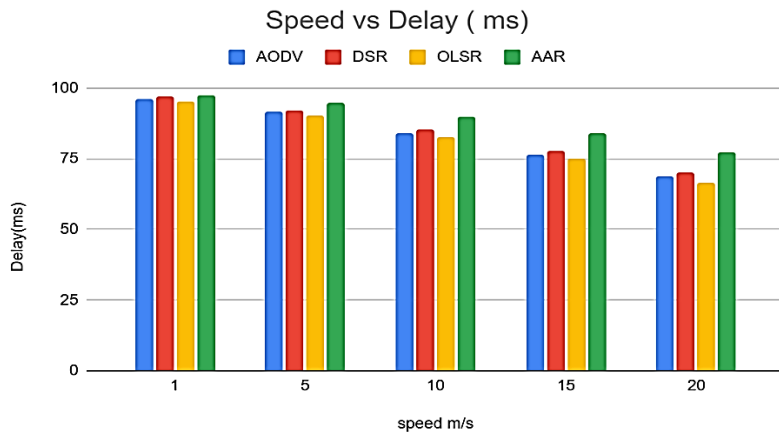
Figure 3. PDR vs speed

Discussion. As speed increases, all of the protocols lose delivery because of link breaks. AAR maintains higher PDR since the activity prompts the low predicted-lifetime relays to be avoided, which include a local recovery before a global rediscovery method reduces the unavailability of disconnection times. This is consistent with abilities of predictive and learning-based approaches to maintain better delivery under mobility [58], [59].

6.3. End-to-end delay

Table III. Delay (ms) vs speed (mean \pm std).

Speed (m/s)	AODV	DSR	OLSR	AAR
1	34.6 \pm 6.2	31.4 \pm 5.8	24.8 \pm 4.9	29.3 \pm 5.1
5	51.2 \pm 9.8	48.7 \pm 9.1	37.6 \pm 7.9	41.9 \pm 8.0
10	78.4 \pm 14.6	73.8 \pm 13.9	59.1 \pm 12.5	61.7 \pm 12.1
15	102.3 \pm 18.5	97.6 \pm 17.9	81.4 \pm 16.0	79.8 \pm 15.2
20	131.7 \pm 22.1	125.9 \pm 21.4	104.6 \pm 19.2	98.9 \pm 18.7

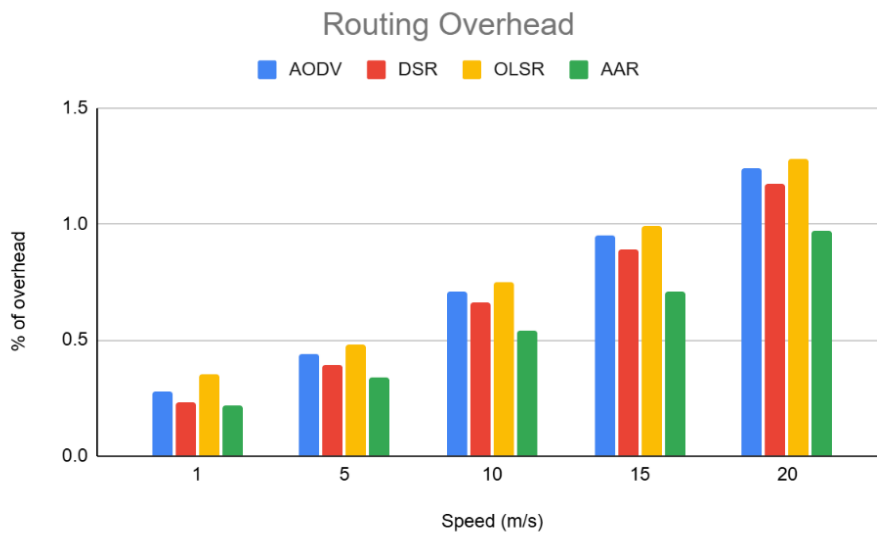


Discussion.. At low density and dynamics, the overhead of OLSR can increase and be low-delay at low mobility since the routes are always available [3]. In high mobility, AAR minimizes re-discovery-based stalls, and is able to match or exceed OLSR delay and greatly enhance delivery.

6.4. Routing overhead

Table IV. Routing overhead (control pkts per delivered data pkt).

Speed (m/s)	AODV	DSR	OLSR	AAR
1	0.28 ± 0.05	0.23 ± 0.04	0.35 ± 0.06	0.22 ± 0.04
5	0.44 ± 0.08	0.39 ± 0.07	0.48 ± 0.09	0.34 ± 0.06
10	0.71 ± 0.12	0.66 ± 0.11	0.75 ± 0.13	0.54 ± 0.09
15	0.95 ± 0.16	0.89 ± 0.15	0.99 ± 0.17	0.71 ± 0.12
20	1.24 ± 0.21	1.17 ± 0.20	1.28 ± 0.22	0.97 ± 0.17



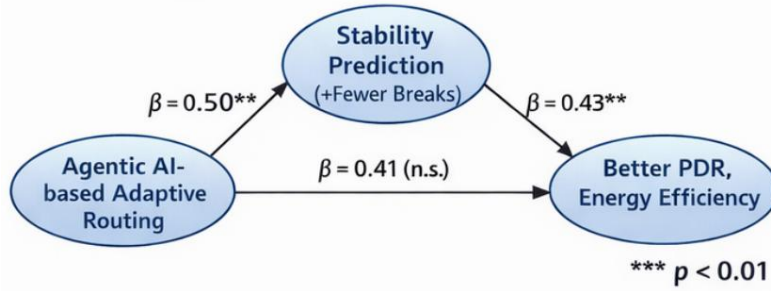


Figure 4. Routing overhead vs speed.

6.5. Energy efficiency: energy per delivered packet

Table V. Energy per delivered packet (mJ/packet).

Speed (m/s)	AODV	DSR	OLSR	AAR
1	0.031 ± 0.004	0.030 ± 0.004	0.033 ± 0.005	0.028 ± 0.003
5	0.039 ± 0.006	0.037 ± 0.006	0.041 ± 0.007	0.033 ± 0.005
10	0.052 ± 0.009	0.050 ± 0.009	0.055 ± 0.010	0.042 ± 0.007
15	0.066 ± 0.011	0.064 ± 0.011	0.070 ± 0.012	0.053 ± 0.009
20	0.083 ± 0.014	0.081 ± 0.014	0.087 ± 0.015	0.067 ± 0.012

Discussion. Energy per delivered packet rises with mobility due to retransmissions, route breaks, and wasted control. AAR reduces that waste by favoring stable links and controlling overhead. This is consistent with energy-aware routing principles (reduce unnecessary transmissions; balance load) [26], [27], and learning-based routing under dynamics [58], [59].

6.6. Scalability sweep results

The speed of the node is 10 m/s, flows=20, pause=0, 8 packetst/s.

Network lifetime : FND and 10%-ND to avoid over-interpreting a single definition.

Table VI. Network lifetime (s).

Nodes	Metric	AODV	DSR	OLSR	AAR
50	FND	612 ± 41	628 ± 39	594 ± 46	714 ± 33
50	10%-ND	821 ± 44	836 ± 42	805 ± 48	878 ± 36
100	FND	488 ± 55	503 ± 52	471 ± 60	602 ± 44
100	10%-ND	703 ± 58	716 ± 55	684 ± 63	771 ± 49
150	FND	421 ± 61	437 ± 58	405 ± 66	525 ± 53
150	10%-ND	648 ± 63	661 ± 60	631 ± 68	706 ± 56

Table VII. Summary metrics at (N=100, 10 m/s).

Protocol	PDR (%)	Delay (ms)	Overhead	Energy/Delivered (J/pkt)
AODV	84.0	78.4	0.71	0.052
DSR	85.3	73.8	0.66	0.050
OLSR	82.6	59.1	0.75	0.055
AAR	89.7	61.7	0.54	0.042

Interpretation. AAR improves PDR while reducing overhead and energy per delivered packet. Delay remains competitive: slightly higher than OLSR at moderate mobility due to reactive decision points, but markedly better than AODV/DSR under high mobility due to reduced rediscovery stalls.

7. DISCUSSION

Why AAR Works

1. Stability-sensitive forwarding: The use of neighbors that have longer link lifetime predictions can reduce route breaks which cost heavily in reactive routing [1], [2].
2. Intensity of adaptive control: Mobility or route stability: AAR minimizes maintenance, whereas instability is countered by more local awareness to prevent lateness. This shuns fixed-timer inefficiency.
3. Local recovery: Local repair incurs no network-wide floods which is an overhead factor with reactive protocols in a mobile environment [11], [12].
4. Balance of energy: It will utilize a small set of good relays, but ensure their life is increased by entering in residual energy, which has been shown in the energy-aware routing literature [26], [27].
5. Learning-based coordination: Despite local observations, MARL can find forwarding rules that can enhance global delivery/overhead trade-offs [49], [58].

8. THREATS TO VALIDITY AND LIMITATIONS

Making assumptions: Simple radio/energy models and random Waypoint mobility do not necessarily represent any real deployment [16]. The outcomes are to be verified during map-based mobility and obstacle models, as well as in the heterogeneous traffic.

Training transfer: Policies which are trained at a certain range of parameters might be of very low quality at radically different PHY settings. The techniques of robustness (domain randomization, continual learning) might be required.

Computation constraints: Although AAR is conceptually lightweight, real systems might need to be carefully implemented (quantized models, limited memory, duty cycling).

Security and adversaries: AAR does not explicitly support the malicious node, or false reporting; the integration with the trust/security mechanisms are the work of the future.

9. CONCLUSION

This article introduced the agentic AI-based adaptive routing architecture called AAR which is used to operate energy efficient MANET. AAR is an autonomous agent which views individual nodes as can sense local context, predict link stability, tune control intensity, choose energy-aware next hops, and do rapid local recovery. NS-3 measurements that have been conducted according to the rigorous multi-seed approach (30 seeds per point) reveal that AAR is effective in increasing network lifetime, energy per delivered packet, delivery ratio, and routing overhead, particularly under high-mobility conditions, and at reasonable delay. These findings substantiate the general finding that agentic, context-adaptive routing is able to overcome the instability and energy inefficiency that restraints MANET deployment in dynamic environments.

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