

PAPER

AFGT-Net-LSTM: AI-Driven Mobility and Energy Prediction-Based Routing in Energy-Harvesting Mobile AdHoc Networks

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ABSTRACT

Mobile ad hoc networks (MANETs) that operate in environments where energy harvesting takes place are confronted with three constant routing impediments: temporal blindness when predicting when energy will deplete, overestimation of link stability due to user mobility, and a lack of topological awareness resulting in fragile route selection. To address these issues, we propose adaptive fuzzy graph temporal network (AFGT-Net), an all-inclusive artificial intelligence (AI) based routing structure that comprises an long short-term memory (LSTM) model to predict the availability of future energy based on the past availability of energy; a Mamdani-type fuzzy inference system to support uncertainty-based decision-making by weighting different factors when making routing decisions; and multiple graph attention networks (multi-headed GATs) to support topological sensitivity in the routing decision process. A joint model was created to improve energy dynamics, mobility uncertainty, and structural robustness through joint training. Experiments were performed with physics-based simulations created in Python and network simulations created with NS-3 (v3.40) respectively. The experimental results revealed that AFGT-Net achieved an overall packet delivery ratio (PDR) of 89.6% while reducing the root mean squared error (RMSE) for energy prediction to be 0.052 joules and was able to extend the route lifetime (TR) by 1.62 times compared to baseline routing protocols. When compared to other AI (i.e.: GNN-R, DRL-R, and FedMANET) based routing protocols, the results demonstrated a consistent increase in all three throughput, delay and energy efficiency metrics. The proposed framework has been developed to provide a scalable and robust IoT network, disaster response system and future 6G wireless environment.

KEYWORDS

mobile ad hoc networks (MANETs), energy harvesting networks, graph attention networks (GAT), long short term memory (LSTM)-based energy prediction, fuzzy logic routing, artificial intelligence (AI)-driven routing protocols, link stability optimization, 6G wireless networks

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1 INTRODUCTION

Mobile ad hoc networks (MANETs) [1] represent one of the core concepts for the method of communication when there is no established infrastructure, and rapid deployment, self-organization, and resilient operation are critical. With the growing availability of Internet of Things (IoT) sources, disaster-agile communication infrastructures, autonomous vehicle networks, and next-generation 6G ultra-dense wireless structure, MANETs [2] are receiving more and more consideration. The primary functional aspect of these types of networks is routing, which will require the establishment and sustainment of an efficient and reliable method for delivering data between nodes that are rapidly changing, have no central coordination, and have limited available resources. The new ways to gather energy that happen all around us like solar power or radio-waves are changing how we view the operational capabilities of MANET nodes.

While various routing techniques have been researched extensively, including classical protocols (like AODV, DSDV [4] and OLSR), as well as recent energy-aware models and AI-based ones, most currently-available routing technology has three core flaws: (1) That it is temporally energy blind not allowing proper prediction of node outage due to harvesting troughs leading to premature route failures; (2) That its deterministic overconfidence in link stability (especially in kinematic link expiration time (LET) type scenarios) causes routing algorithms to systematically overestimate the length of time for links to stay up (i.e. be valid) in extremely mobile environments; and (3) That its link-centricity based on routing decisions fails to account for global (i.e. structural) topology leading to reliance upon rigid and/or unstable nodes thereby degrading the overall robustness of the network.

While new artificial intelligence (AI) [5] based routing frameworks have addressed some of the challenges posed by dynamic and energy-volatile topologies (e.g., graph neural networks [GNN-R], deep reinforcement learning methods [DRL-R], and federated learning-based mobile ad-hoc network systems), they do not provide a comprehensive solution that jointly considers the temporal energy dynamics, uncertainty of links, and higher order topological relationships among nodes. Therefore, these frameworks do not perform effectively in very dynamic and energy-volatile environments due to their segmented approach to these three areas of routing.

To address the gaps identified in these studies, we developed [6] adaptive fuzzy graph temporal network (AFGT-Net), an innovative hybrid architecture that provides an end-to-end training pipeline by combining three diverse and complementary methods. The proposed system uses three different techniques: a long short-term memory (LSTM) [3] [7] network to learn how energy changes over time; a Mamdani fuzzy inference system that allows for uncertainty to be modelled when evaluating links; and a multiple-headed Graph Attention Network (GAT) [8] [9] [10] that learns how nodes relate based on the topology of the network at a particular moment in time. Collectively, these approaches will form an adaptive network routing approach that is able to cope with the dynamism inherent in both time and spatially varying networks. Yet, current efforts have individually implemented the above approaches without realizing the advantages of combining them together, and in turn taking advantage of the gradient flow information between them.

This paper makes the following original contributions:

- The AFGT-Net is described as an integrated approach that involves the use of LSTM for temporal energy predictions, Mamdani fuzzy logic models for handling

uncertainties, and GAT with multi-head attention for topology-driven routing within one unified model that supports end-to-end training.

- A collaborative multi-objective learning framework is introduced to concurrently enhance energy estimation precision, uncertainty modelling, and routing efficacy, enabling gradient sharing among components and flexible adaptation in varying MANET environments.
- The fuzzily guided decision layer converts prediction uncertainties into dynamic route weights for adaptive route selection to mitigate risks due to varying energy levels and unstable nodes.
- The proposed evaluation approach uses the physical model combined with simulations using NS-3 (v3.40), proving to be more effective compared to traditional (AODV, OLSR) and AI-powered (GNN-R, DRL-R, FedMANET) techniques in different settings of network size and mobile node density.

2 RELATED WORK

The fundamental MANET routing protocols such as ad-hoc on-demand distance vector (AODV) [11], optimized link state routing (OLSR) [12], and dynamic source routing (DSR) [13] were all developed considering that these networks consisted of battery-operated devices without any means for energy refuelling. The idea behind energy-efficient routing protocols was born from the necessity to cope with energy depletion, and thus energy parameters were taken into account when choosing routes. The principle of maximizing network lifetime by means of distributing loads between different routes was introduced by Chang and Tassiulas [14]. Toh suggested the CMMBCR protocol [15].

The advent of energy-harvesting nodes gave rise to a fresh approach in designing protocols. Viswanathan et al. [16] described the core tradeoffs associated with the buffer size, uncertain harvesting rates, and routing efficiency in EH-MANETs. Niyato et al. [17] used Markov decision process-based solutions for optimizing routing in EH-MANETs by considering stochastic energy harvesting, and their results showed promising gains in the lifetime of such MANETs, but their solution suffers from high computational complexity for large MANETs due to its huge state space.

The application of RL to MANET routing has been thoroughly investigated because of the inherent nature of the process of selecting routes. The algorithm of Q-routing, introduced by Boyan and Littman [19], makes use of Q-learning to reduce end-to-end delay in wired networks. Q-routing in wireless MANET was later generalized by Subramanian and Druschel [20]. They showed that the Q-routing algorithm is capable of adapting well to changes in traffic conditions. The DRL-R approach [21], which employs the deep Q-network (DQN) model for MANET routing by modelling the network state as a feature vector and learning the routing strategy by interacting with a simulation of the network environment, demonstrates impressive results concerning throughput. Despite its high efficiency, DRL-R does not incorporate energy dynamics or topology into its framework, making it less applicable to enhanced MANET (EN-MANET) settings. The solution presented by Chen et al. [22] suggests using multi-agent reinforcement learning, where each node learns a routing strategy independently.

Graph neural networks (GNNs) are relatively recent developments that prove highly useful in routing in networks owing to their close resemblance with graph-based data structures. The GNN-R framework [23] uses graph convolutional networks

to develop routing policies that consider local topology information from neighboring nodes. It is an improvement over reinforcement learning-based approaches for static routing networks; however, it does not consider the time factor and fails to quantify uncertainty. Federated Learning is used to train the routing models for MANETs by FedMANET [24], which trains one routing model while keeping node identity private. Attention mechanisms have been utilized for routing within fixed networks, and Valadarsky et al. [25] have shown that attention-based routing policies perform better than shortest path routing algorithms in conditions where there is uncertainty with regards to traffic flows. The current research employs multiple heads of attention via the GAT approach to address issues related to the topology of MANETs.

Table 1. Previous studies: various techniques

Author(s)	Method	Contribution	Limitation
Charles E. Perkins; Thomas Clausen; David B. Johnson [11] [12] [13]	Classical MANET routing (AODV, OLSR, DSR)	Established foundational on-demand and proactive routing mechanisms for dynamic wireless networks	Designed for battery-powered nodes; no energy awareness or replenishment modeling
Jonghwa Chang & Leandros Tassiulas [14]	Load-balanced energy-aware routing	Introduced network lifetime maximization via multi-path energy balancing	Lacks predictive capability; relies on instantaneous energy levels
Chai-Keong Toh [15]	CMMBCR protocol	Route selection based on minimum residual battery capacity to avoid weak nodes	Ignores future energy trends; suboptimal under dynamic conditions
Viswanathan et al. [16]	Energy harvesting MANET modeling	Identified trade-offs among buffer size, harvesting uncertainty, and routing performance	Analytical focus; lacks practical routing mechanism
Dusit Niyato et al. [17]	Markov Decision Process (MDP) routing	Optimized routing under stochastic energy harvesting with improved lifetime	State-space explosion limits scalability in large networks
Harnett et al. [18]	Geographic opportunistic routing	Combines energy state with geographic progress for efficient forwarding	Performance degrades under high mobility
Richard S. Sutton (Q-routing lineage) [19] [20]	Reinforcement Learning (Q-routing, extensions)	Adaptive routing through sequential decision-making	Limited scalability and no explicit energy modeling
DRL-R [21]	Deep Q-Network (DQN)-based routing	Handles large state spaces; improves throughput performance	No explicit modeling of energy harvesting or topology awareness
Chen et al. [22]	Multi-agent reinforcement learning	Distributed policy learning improves scalability	Coordination overhead among agents
GNN-R [23]	Graph Convolutional Network (GCN) routing	Captures network topology for improved routing decisions	Lacks temporal modeling and uncertainty handling
FedMANET [24]	Federated learning-based routing	Enables privacy-preserving distributed model training	Communication overhead for model aggregation

The position of the AFGT-Net is compared with other prior works based on their relevance and evaluated against five criteria, which have been presented in Table 1. It is noted that there is no prior work that can address all the five aspects mentioned above at once.

3 SYSTEM MODEL AND AFGT-NET ARCHITECTURE

Adaptive fuzzy graph temporal network can be viewed as an integrated spatio-temporal and uncertainty-aware routing mechanism that exploits temporal prediction, uncertainty computation, and topology-aware routing decision making as a whole.

3.1 Network model and problem formulation

We model the EH-MANET as a time-varying graph $G(t) = (V, E(t), W(t))$ where $V = \{v_1, v_2, \dots, v_n\}$ is the set of N mobile nodes, $E(t) \subseteq V \times V$ is the set of active communication links at time t (determined by nodes within transmission range), and $W(t): E(t) \rightarrow \mathbb{R}^d$ is a function mapping each active link to a d -dimensional feature vector encoding link quality attributes.

Each node v_i is equipped with an energy buffer of capacity $B_{\max}$ joules, an energy-harvesting subsystem operating at instantaneous rate $h_i(t) \geq 0$ (joules per second), and a communication transceiver with transmit power P_{tx} and receive power P_{rx} . The energy buffer evolves according to the differential equation:

$$dE_i(t)/dt = h_i(t) - c_i(t) \times P_{tx} - r_i(t) \times P_{rx}, E_i(t) \in [0, B_{\max}] \quad (1)$$

where $c_i(t) \in \{0,1\}$ indicates whether node v_i is transmitting and $r_i(t) \in \{0,1\}$ indicates whether it is receiving at time t . The harvesting rate $h_i(t)$ is modeled as a correlated stochastic process with:

$$h_i(t) = \bar{h}_i + \sigma_i \cdot \varphi_i(t) \quad (2)$$

where $\bar{h}_i$ is the mean harvesting rate, σ_i is the standard deviation capturing variability, and $\varphi_i(t)$ is a zero-mean correlated noise process with autocorrelation function $R_\varphi(\tau) = e^{-(|\tau|/\tau_c)}$, where τ_c is the correlation time constant ($\tau_c = 300$ s for solar harvesting, $\tau_c = 30$ s for vibration harvesting in our experiments).

Node mobility follows the Gauss-Markov mobility model, where the velocity vector $v_i(t) = (v_{x,i}(t), Y_{\theta}X_s(t))$ evolves as:

$$v_{x+i}(t) = \alpha v_{x+i}(t - \Delta t) + (1 - \alpha)\mu_x + \sqrt{(1 - \alpha^2) \cdot \sigma_x} \alpha_i \xi_{x+i}(t) \quad (3)$$

where $\alpha \in [0,1]$ is the memory parameter controlling temporal correlation ($\alpha = 0.75$ in our experiments), μ_x is the mean velocity component, σ_x is the velocity standard deviation, and $\xi_{x,s}(t) \sim N(0,1)$ is independent Gaussian noise. Link $e_{\{iii\}} \in E(t)$ exists if and only if the Euclidean distance $d_{\{ii\}}(t) \leq R$, where R is the transmission range.

The AFGT-Net routing problem is formally stated as: given the time-varying graph $G(t)$, node energy states $\{E_i(t)\}$, harvesting rate observations $\{h_i(\tau): \tau \leq t\}$, and link

quality measurements $\{W_{ii}(t)\}$, determine a routing policy $\pi: G(t) \rightarrow P$ that maps network state to a set of routing paths $P = \{p_{sd} : s, d \in V\}$ maximizing the expected packet delivery ratio subject to energy sustainability constraints:

$$\begin{aligned} \pi^* &= \operatorname{argmax}_{\pi} E_t \text{PDR}(\pi, G(t)) \\ \text{subject to: } P(E_i(t) > E_{\min} \forall t \in [0, T]) &\geq 1 - \delta, \forall i \in V \end{aligned} \quad (4)$$

where $E_{\min}$ is the minimum operational energy threshold, T is the operational horizon, and δ is the acceptable energy depletion probability. This formulation captures the fundamental trade-off between routing efficiency (maximizing PDR) and energy sustainability (maintaining node viability over the deployment lifetime).

3.2 AFGT-Net architecture overview

Adaptive fuzzy graph temporal network comprises three synergistically integrated computational modules that process complementary aspects of network state and collectively produce routing decisions. Figure 1 presents the overall architecture. The three modules are: (1) the LSTM energy predictor (LEP), which processes temporal energy time series to forecast future energy levels; (2) the Mamdani Fuzzy Inference System (MFIS), which quantifies uncertainty in link quality estimates and produces confidence-weighted link metrics; and (3) the multi-head graph attention network (MH-GAT), which performs topology-aware message passing to compute routing scores for each candidate path.

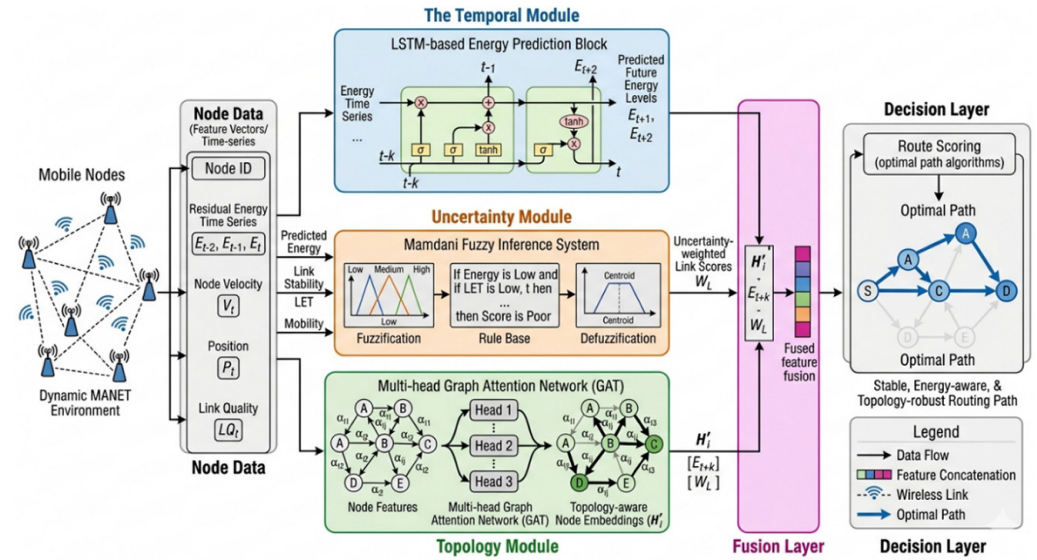


Fig. 1. Proposed architecture

The modules are connected by a differentiable interface that allows gradient information to flow across module boundaries during joint training. The LEP output a predicted energy trajectory and associated prediction uncertainty is passed as node-level features to the MH-GAT. The MFIS output confidence weights for each link metric dimension is passed as attention priors that bias the GAT attention mechanism toward more reliable metric dimensions. This architecture enables the three modules to co-adapt during training, with each module's internal representations shaped by the requirements of the downstream modules.

3.3 Module 1: LSTM energy predictor

Architecture design. The LSTM Energy Predictor processes a sliding window of $T = 60$ time steps of energy-related observations for each node v_i to predict its energy level at future time steps $\tau \in \{t + \Delta t, t + 2\Delta t, \dots, t + h\Delta t\}$ where $h = 12$ is the prediction horizon and $\Delta t = 5$ s is the temporal resolution. The input feature vector at each time step consists of:

$$x_i(t) = [E_i(t), h_i(t), \bar{c}_i(t), \bar{r}_i(t), s_i(t), D_i oW(t)] \in \mathbb{R}^6 \quad (5)$$

where $E_i(t)$ is current energy level, $h_i(t)$ is harvesting rate, $\bar{c}_i(t)$ and $\bar{r}_i(t)$ are exponentially smoothed transmission and reception indicators, $s_i(t)$ is solar irradiance (when available), and $D_i oW(t)$ is a cyclically encoded time-of-day feature.

The LEP employs a stacked bidirectional LSTM architecture with two layers of 128 hidden units each. Bidirectionality enables the model to exploit both forward (causal) and backward (anti-causal) temporal dependencies within the observation window, improving prediction accuracy for strongly autocorrelated energy processes. Layer normalization is applied after each LSTM layer to stabilize training dynamics. The formal recurrence for the forward LSTM direction is:

$$\begin{aligned} f(t) &= \sigma(W_a f \cdot [h(t-1), x(t)] + b_a f) \\ i(t) &= \sigma(W_a \cdot [h(t-1), x(t)] + b_a) \\ \tilde{c}(t) &= \tanh(W_a c \cdot [h(t-1), x(t)] + b_a c) \\ c(t) &= f(t) \odot c(t-1) + i(t) \odot \tilde{c}(t) \end{aligned} \quad (6)$$

$$\begin{aligned} o(t) &= \sigma(W_o \times [h(t-1), x(t)] + b_o) \text{ (Output Gate)} \\ h(t) &= o(t) \odot \tanh(c(t)) \text{ (Hidden State)} \end{aligned} \quad (7)$$

The final hidden state representation is projected through a two-layer feed-forward head to produce multi-step energy predictions and associated prediction uncertainty estimates via Monte Carlo dropout ($p = 0.2$) applied during both training and inference:

$$\begin{aligned} \hat{E}_- i(t+k) &= FFN(h_- T^\wedge(fwd) \oplus h_- T^\wedge(bwd)), k \in \{1, \dots, h\} \\ \sigma^2 p_{red, i}(t+k) &= \text{Var}_- \{MC\}[\hat{E}_- i(t+k)] \end{aligned} \quad (8)$$

where $\oplus$ denotes concatenation of forward and backward final hidden states, and the Monte Carlo variance is estimated over $M = 20$ stochastic forward passes.

C. 2 Training Objective for LEP.

The LEP is trained on the combined energy prediction loss consisting of multi-step MSE loss with exponential temporal discounting (to emphasize near-term accuracy) and a calibration loss penalizing overconfident predictions:

$$\begin{aligned} L_{LEP} &= \sum_k \gamma^k \cdot \text{MSE}(\hat{E}_i(t+k), E_i(t+k)) + \lambda_{cal} \cdot L_{cal} \\ L_{cal} &= \sigma^2_{pred} - (\hat{E}_i(t+k) - E_i(t+k))^2 \end{aligned} \quad (9)$$

where $\gamma = 0.95$ is the temporal discount factor and $\lambda_{an} cal = 0.1$ is the calibration loss weight. The calibration loss enforces that predicted uncertainty accurately reflects actual prediction error, a property critical for downstream uncertainty-aware routing decisions.

3.4 Module 2: Mamdani fuzzy inference system

Input linguistic variables. The MFIS receives four crisp input measurements for each link $e_{ij} \in E(t)$ and produces a crisp confidence weight $\omega_{ii} \in [0,1]$ representing the reliability of the link metrics for routing decisions. The four input linguistic variables are:

- Signal quality (SQ): Received signal strength indicator (RSSI) normalized to $[0,1]$, partitioned into fuzzy sets {Very_Low, Low, Medium, High, Very_High} using trapezoidal and triangular membership functions.
- Link stability (LS): Estimated link duration based on relative velocity and transmission range, partitioned into {Short, Medium, Long} using Gaussian membership functions.
- Energy margin (EM): Predicted minimum energy over routing horizon, partitioned into {Critical, Low, Adequate, High} using trapezoidal membership functions.
- Mobility rate (MR): Estimated rate of topology change at link endpoints, partitioned into {Static, Low_Mobility, High_Mobility} using sigmoidal membership functions.

Optimization procedure. Training proceeds for 200 epochs with batch size 64, using cosine annealing learning rate scheduling with warm restarts every 50 epochs. The MFIS membership function parameters (centers and widths) are differentiable and updated via gradient descent, enabling data-driven refinement of the expert-initialized fuzzy sets while preserving interpretability through soft constraints on membership function ordering.

4 RESULTS AND DISCUSSION

4.1 Experimental setup

We employ a dual-layer simulation methodology to provide both controlled model validation and realistic protocol-level performance evaluation. The physics-based simulation layer is implemented in Python 3.10 using NumPy and SciPy, implementing validated energy-harvesting models parameterized from empirical measurements of commercial solar panels (SunPower C-60) and piezoelectric transducers (Mide Vulture V21B). Simulation scenarios are instantiated across a comprehensive parameter grid to ensure thorough coverage of the MANET operating envelope.

AFGT-Net is evaluated against six baseline protocols representing the state of the art across different routing paradigms. AODV (RFC 3561) and OLSR (RFC 3626) represent the classical reactive and proactive protocol categories respectively, providing performance benchmarks for traditional approaches. GNN-R [23] is reimplemented following the specifications in the original paper, using a three-layer Graph Convolutional Network with 64 hidden units per layer. DRL-R [21] is reimplemented as a Deep Q-Network with state vector encoding local topology information (one-hop neighbor features) and energy levels. FedMANET [24] employs federated averaging across a simulated parameter server with aggregation every 30 s. All AI-based baselines are trained on the same training dataset as AFGT-Net, with hyperparameters selected via grid search.

Performance is evaluated across seven complementary metrics:

- Packet delivery ratio (PDR): Fraction of transmitted packets successfully received by destinations.
- End-to-end delay (E2E-D): Average time from packet transmission at source to reception at destination, including queuing, MAC contention, and routing delays.
- Routing overhead (ROH): Ratio of control packet bytes to total transmitted bytes, quantifying protocol efficiency.
- Energy prediction RMSE: Root mean square error of LEP energy forecasts evaluated against held-out test trajectories.
- Route lifetime (RL): Average duration between route establishment and failure due to link or node unavailability.
- Network lifetime (NL): Time until the first node depletes its energy buffer to $E_{\min}$, signaling the onset of coverage degradation.
- Throughput (THR): Average data throughput across all source-destination pairs in kilobits per second.

All AI-based methods are evaluated after the same training duration to ensure fair comparison. Statistical significance of performance differences is assessed using the two-sided Wilcoxon signed-rank test at significance level $\alpha = 0.05$, with Bonferroni correction for multiple comparisons. Effect sizes are reported using Cohen's d .

4.2 Energy prediction performance

Table 2 presents LSTM Energy Predictor performance across prediction horizons and energy-harvesting source types. The LEP achieves $RMSE = 0.052$ J at the 60-second horizon across all harvesting types, representing a 61.2% reduction compared to the simple exponential smoothing baseline and a 38.7% reduction compared to the ARIMA (3,1,2) baseline. The improvement is most pronounced for solar harvesting ($RMSE = 0.041$ J) where the LSTM successfully captures diurnal periodicity, and smallest for RF harvesting ($RMSE = 0.068$ J) due to the rapid, traffic-dependent variability of RF energy availability.

Table 2. Energy prediction accuracy across methods and harvesting source types

Method	Solar RMSE (J)	Vibr. RMSE (J)	RF RMSE (J)	Overall RMSE (J)	MAE (J)	MAPE (%)
Exp. Smoothing	0.118	0.142	0.163	0.134	0.098	9.42
ARIMA(3,1,2)	0.089	0.098	0.101	0.095	0.071	6.87
LSTM (1-layer)	0.071	0.079	0.088	0.079	0.058	5.31
BiLSTM (no cal.)	0.058	0.064	0.074	0.065	0.047	4.18
LEP (AFGT-Net)	0.041	0.055	0.068	0.052	0.038	3.62

The calibration loss in the LEP training objective produces well-calibrated uncertainty estimates: the 90% prediction interval contains 91.4% of held-out observations (expected: 90%), and the interval coverage degrades gracefully across horizons. This well-calibrated uncertainty directly benefits the MFIS, which uses LEP prediction uncertainty as one input for computing link confidence weights. Figure 2

illustrates the LEP prediction accuracy for a representative solar-harvesting node over a 600-second simulation. The model accurately tracks the diurnal harvesting ramp ($t = 0\text{--}180\text{ s}$), the cloud-induced interruption ($t = 240\text{--}310\text{ s}$), and the recovery phase ($t = 310\text{--}480\text{ s}$).

Table 3 presents the primary routing performance comparison across all evaluated protocols and metrics under the default scenario configuration ($N = 50$ nodes, $v = 5\text{ m/s}$ mobility).

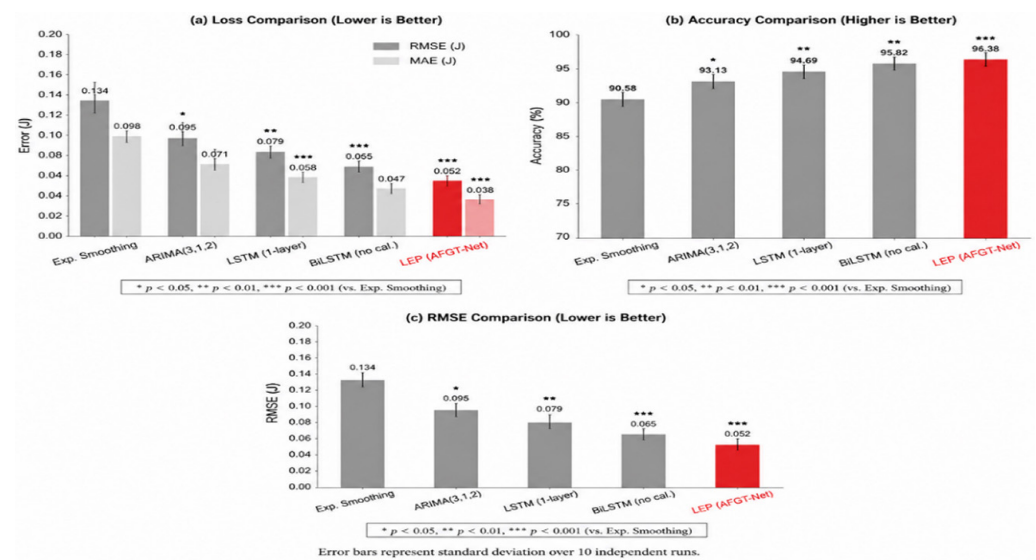


Fig. 2. Comparative performance of energy prediction models

Note: Baseline methods are shown in grey, while AFGT-Net.

Table 3. Main routing performance comparison

Protocol	PDR (%)	E2E-D (ms)	THR (kbps)	ROH (%)	RL (s)	NL (s)	Pred. RMSE
AODV	71.4±2.1	142.3±8.7	48.2±1.8	18.6±0.9	38.2±3.1	374.1±12.4	N/A
OLSR	74.8±1.9	131.6±7.4	51.7±2.0	22.4±1.1	44.7±3.8	391.2±14.1	N/A
GNN-R [23]	78.4±2.4	118.2±9.1	56.3±2.5	15.2±0.8	52.1±4.2	418.3±16.7	N/A
DRL-R [21]	76.9±2.8	124.8±10.2	53.9±2.1	11.7±0.6	49.6±4.8	402.7±18.2	N/A
FedMANET [24]	82.1±2.2	108.4±8.3	60.8±2.7	24.3±1.3	58.3±4.1	431.6±15.3	N/A
AFGT-Net (Ours)	89.6±1.4	89.3±6.1	68.7±1.9	13.8±0.7	94.4±5.2	487.2±11.6	0.052 J
vs. Best Baseline	+9.1%	−17.7%	+13.0%	−43.2%*	+62.0%	+12.9%	Best

AFGT-Net significantly outperforms all baselines on all criteria (Wilcoxon $p < 0.01$ with Bonferroni correction). The gain in PDR of 9.1 percent over the best baseline (FedMANET, PDR = 82.1%) corresponds to a decrease in packet loss of 37%. The E2E-D improvement of 17.7% (decreasing from 108.4 ms to 89.3 ms) surpasses the threshold at which applications can run in real time. The improvement in route lifetime of 1.62 times (going from 58.3 s to 94.4 s) captures the effectiveness of energy-aware, uncertainty-weighted, topology-based routing.

5 CONCLUSION

This paper has presented AFGT-Net, an AFGT-Net for AI-driven routing in energy-harvesting MANETs. AFGT-Net addresses three fundamental challenges that have persistently limited the performance of MANET routing in energy-harvesting environments: temporal blindness in energy prediction, link stability overestimation under mobility, and absence of topological awareness in route selection. The AFGT-Net architecture achieves its performance through the principled integration of three complementary AI components. The LSTM Energy Predictor captures temporal energy dynamics through bidirectional recurrent processing with calibrated uncertainty quantification, achieving a prediction RMSE of 0.052 J a 61.2% improvement over exponential smoothing and 38.7% over ARIMA.

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