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Adaptive Hybrid Routing for Wireless Mesh Networks in Smart Grid: An ML-Driven Framework Integrating RPL and GPSR

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Abstract
The integration of communication networks into smart grids introduces stringent requirements for reliability, low latency, scalability, and energy efficiency. Existing routing protocols — the Routing Protocol for Low-Power and Lossy Networks (RPL) and Greedy Perimeter Stateless Routing (GPSR) exhibit complementary strengths and weaknesses across varying network conditions. This paper proposes an Adaptive Hybrid Routing Framework (AHRF) that integrates RPL and GPSR under a machine learning (ML)-driven decision engine. The system dynamically selects the most suitable protocol based on real-time network features including link quality, node degree, residual energy, queue occupancy, and traffic load. We present rigorous mathematical models of both protocols, formulate a composite utility function capturing trade-offs among packet delivery ratio (PDR), end-to-end delay, throughput, and energy consumption, and integrate a Random Forest classifier for adaptive protocol selection. The framework is validated through a custom discrete-event packet-level simulator implementing log-distance path loss with shadowing over a 500×500 m wireless mesh with up to 200 randomly deployed nodes across four operational scenarios. Results demonstrate that the proposed Hybrid-ML framework achieves PDR improvements of up to 8.6% over standalone RPL in the density scenario and up to 110.7% over GPSR under node failure conditions, while achieving 27.4% lower energy consumption per packet than GPSR in dense deployments. The Random Forest classifier achieves 95.6% cross-validation accuracy. Feature importance analysis reveals that average SNR (29.9%), SNR standard deviation (20.8%), and path diversity (15.9%) are the dominant predictors of optimal protocol selection, providing interpretability to the ML component. The findings demonstrate that ML-based hybridization of complementary routing protocols offers a resilient and energy-efficient routing solution for next-generation smart grid neighborhood area networks.

Keywords: Routing Protocol, GPSR, RPL, Hybrid Routing, Smart Grid, Machine Learning, Wireless Mesh Network, IoT

Introduction
Modern power systems are evolving into smart grids — cyber-physical infrastructures characterized by large numbers of interconnected devices communicating over real-time links. Within neighborhood area networks (NANs), wireless mesh networks (WMNs) offer a practical backbone owing to their low cost and self-organizing nature. These networks operate under resource constraints including limited processing power and battery capacity, while communicating over low-bandwidth links subject to interference and shadowing. Efficient routing is critical in such settings, as it directly impacts packet delivery, end-to-end delay, scalability, and energy consumption [1].

Two routing protocols have been widely deployed for IoT and smart grid integration. The Greedy Perimeter Stateless Routing (GPSR) protocol leverages geographic forwarding to enable lightweight routing with minimal state information, making it suitable for dense deployments and energy-constrained devices [2]. However, GPSR struggles under high congestion, sparse topologies, and in scenarios where greedy forwarding fails due to routing voids. RPL, developed and standardized by the IETF for IPv6-based IoT communications, constructs hierarchical Directed Acyclic Graphs (DODAGs) to manage traffic flows in Low-Power and Lossy Networks (LLNs) [3]. RPL offers robustness and broad applicability but incurs higher delay due to route upkeep and performs poorly under congestion and uneven load distribution.

Empirical studies and field deployments show that communication failures and congestion episodes in NANs arise not only from insufficient bandwidth but from inefficient routing adaptation under varying density and link interference [4,5]. The weaknesses of these individual protocols motivate the exploration of hybrid routing strategies that combine the strengths of both approaches.

This paper addresses this gap by proposing a Random Forest-driven hybrid routing framework that dynamically selects between GPSR and RPL based on node-level features. The goal is to demonstrate how adaptive, data-driven routing mechanisms can significantly improve PDR, delay, throughput, and energy efficiency in IoT and smart grid applications. The main contributions of this work are:

- A formal mathematical model of the hybrid routing framework integrating RPL and GPSR under a unified utility function.
- A Random Forest classifier trained on simulation-derived features that achieves 95.6% crossvalidation accuracy in protocol selection.
- A rigorous packet-level discrete-event simulation framework implementing IEEE 802.15.4compatible channel models across four operational scenarios.
- Comprehensive performance evaluation demonstrating the conditions under which each protocol excels and where hybrid switching provides measurable gains.
- Feature importance analysis providing interpretability to the ML decision engine.

Literature Review

Geographic Routing in IoT and Smart Grid Networks

Geographic routing protocols such as GPSR have been extensively studied in wireless sensor and IoT networks. GPSR employs greedy forwarding to transmit packets to the neighbor closest to the destination and uses perimeter routing when greedy forwarding fails due to voids [2]. Its ability to operate without global topology knowledge and its reliance on local geographic information reduces overhead and makes it attractive for resource-constrained devices. However, GPSR is vulnerable in environments with high congestion or unreliable links. Enhanced variants such as E-GPSR address this by incorporating trust mechanisms and link reliability into routing decisions, improving delivery ratio and resilience against malicious behavior [6]. Despite these improvements, GPSR continues to suffer under heavy traffic loads and dynamic topologies, limiting its scalability in dense IoT deployments.

RPL for Low-Power and Lossy Networks

RPL has emerged as the IETF standard for IPv6-based IoT communications [3]. RPL organizes nodes into DODAGs, providing support for multipoint-to-point and point-to-point traffic flows via an objective function (OF) that minimizes a rank metric derived from expected transmission count (ETX). Its flexibility and standards compliance have led to wide adoption in IoT and smart grid systems. However, RPL exhibits poor performance under congestion and uneven load distribution. Studies demonstrate that conventional RPL experiences high packet loss and excessive energy consumption when subjected to dense device deployments and complex traffic patterns [7]. Load-aware extensions such as Learning Automata-based RPL (LALA-RPL) adjust routing decisions by incorporating buffer occupancy and residual energy into the objective function, achieving improvements in delivery and latency [8].

Machine Learning in Network Routing

The literature shows growing interest in hybrid and machine learning-based approaches to routing [9]. Rule-based hybrids often rely on utility functions that weigh performance indicators such as delivery ratio, delay, and energy consumption. More recently, machine learning-driven routing has been explored to automate decision-making. Random Forest classifiers are particularly effective in such contexts because they can learn from diverse features including node degree, average signal-to-noise ratio, queue length, and residual energy, handling noise and nonlinear feature interactions robustly [9,10].

Research Gap

Despite these advancements, a clear research gap persists. Existing protocols are insufficient to simultaneously satisfy the demands of reliability and energy efficiency in smart grid NANs across dynamic operational conditions. Rule-based hybrids improve adaptability but remain limited by predefined thresholds, while ML-based routing has not been systematically integrated into hybrid GPSR-RPL schemes in a way that is both interpretable and validated through independent simulation. This paper addresses this gap by developing a Random Forest-driven hybrid framework validated through rigorous packet-level simulation.

Methodology

Smart Grid Communication Scenario

This study considers a Neighborhood Area Network (NAN) segment of a smart grid, comprising smart meters and sensor nodes communicating through a WMN. Each node functions as both a sensing device and a data-forwarding relay, forming a multi-hop, self-organizing topology that supports upward data exchange from field devices to a central data concentrator (sink node).

The network operates within a 500×500 m region, representative of urban distribution feeders. Two traffic classes are modeled: periodic metering data emphasizing reliability, and event-driven control data emphasizing low latency. Four operational scenarios are evaluated:

Scenario **Description**

- Baseline No failures, moderate load (0.1 pkt/s)
- Failures Random node failure (20% node loss)
- Congestion High traffic rate (0.4 pkt/s)
- Density Dense deployment (300×300 m area)

Simulation Environment

All simulations are implemented in a custom Python discrete-event simulator that models packet-level behavior including generation, queuing, multi-hop forwarding, transmission delay, propagation delay, and energy consumption. The simulator is validated against known analytical results for log-distance path loss and Poisson traffic models.

Key simulation parameters are summarized in Table I.

Parameter	**Value**
Nodes N	150–200
Area	500×500 m (300×300 m for density)
Simulation duration	100–300 s
Packet size	100 bytes
Data rate	250 kbps
Tx power	0 dBm
Noise floor	−100 dBm
Path loss exponent	3.0
Shadowing std. dev.	4 dB
SNR threshold	10 dB
Packet rate λ	0.1–0.4 pkt/s
Epoch duration	5 s
Switching cooldown	15 s
Hysteresis threshold	Δ 0.05
Max queue length	50 packets
Initial node energy	10 J
Seeds per configuration	3

Table 1: Simulation Parameters

Mathematical Models

Network and Channel Model

Nodes are randomly deployed in the simulation area following a uniform spatial distribution. The received SNR between nodes i and j under log-distance shadowing is:

$$SNR_{ij} = P_t - PL(d_{ij}) + X_\sigma - N_0$$

$$PL(d_{ij}) = PL_0 + 10n\log_{10}\left(\frac{d_{ij}}{d_0}\right)$$

where P_t = 0 dBm is the transmission power, PL_0 is the free-space reference path loss at d_0 = 1 m:

$$PL_0 = -20\log_{10}\left(\frac{\lambda}{4\pi d_0}\right)$$

c with $\lambda = f$ the wavelength at f = 2.4 GHz, n = 3.0 is the path loss exponent, $X_\sigma \sim N(0, \sigma^2)$ represents shadowing with σ = 4 dB, and N_0 = −100 dBm is the noise floor. A link (i, j) is valid if:

$$SNR_{ij} \geq \gamma_{th} = 10\ dB$$

The adjacency matrix derived from this condition defines the mesh connectivity graph $G = (V, E)$.

Traffic and Queue Model

Each non-sink node generates packets according to a Poisson process with rate $\lambda\ pkt/s$. The inter-arrival time between packets follows an exponential distribution with $mean\ 1/\lambda$. Packets are queued with maximum capacity $Q_{max} = 50$. Transmission time per hop is:

$$\tau_{tx} = \frac{8l}{R}$$

where $l = 100\ bytes$ is the packet size and $R = 250{,}000$ bps is the data rate. A packet is dropped if the buffer overflows or if no valid route exists.

Energy Model

The first-order radio energy model is used:

$$E_{tx}(l, d) = E_{elec} \cdot l + \varepsilon_{amp} \cdot l \cdot d^k$$

$$E_{rx}(l) = E_{elec} \cdot l$$

where E_{elec} = 50 nJ/bit accounts for electronics energy, $\varepsilon_{amp} = 100\ pJ/bit/m^2$ is the amplifier energy coefficient, and κ = 2 is the energy path loss exponent. Total energy consumed per packet along a path of H hops:

$$E_{path} = \sum_{h=1}^{H} [E_{tx}(l, d_h) + E_{rx}(l)]$$

RPL Protocol Model

RPL organizes nodes into a DODAG rooted at the sink (node 0). Link cost is expressed as Expected Transmission Count:

$$ETX_{ij} = \frac{1}{p_{succ,ij}}$$

where $p_{succ,ij}$ is estimated from the observed link SNR:

$$p_{succ,ij} = \min\left(0.99, \max\left(0.1, 1 - e^{\frac{-SNR_{ij}}{10}}\right)\right.$$

Node rank is computed via Objective Function Zero (OF 0):

$$Rank_i = \min_{j \in N(i)} \{Rank_j + \lceil ETX_{ij} \times MinHopRankIncrease \rceil\}$$

with $Rank_{sink} = 0$ and $MinHopRankIncrease = 256$. The DODAG is constructed via a Bellman-Ford relaxation that iterates until no rank improvements are possible. Each non-sink node forwards packets to its parent — the neighbor with minimum rank.

GPSR Protocol Model

Each node forwards packets to the neighbor closest to the destination (sink):

$$v^* = arg \min_{w \in N(u)} \|x_w - x_{sink}\|$$

When no closer neighbor exists (void condition), perimeter routing selects the neighbor with the highest SNR as a fallback:

$$v_{perimeter} = arg \max_{w \in N(u)} SNR_{uw}$$

A hop limit of $H_{max} = 2\sqrt{N} + 5$ is enforced to prevent forwarding loops.

Expected hop count under greedy forwarding:

$$\mathbb{E}[H_{GPSR}] \approx \frac{\|x_s - x_{sink}\|}{\bar{r}_{eff}}$$

where $\bar{r}_{eff}$ is the mean progress per hop derived from node density.

Hybrid Utility and Switching Function
Each protocol p ∈ {RPL, GPSR} is assigned a composite utility:

$$U_p = w_1 \cdot PDR_p - w_2 \cdot \frac{D_p}{D_{max}} - w_3 \cdot \frac{E_p}{E_{max}}$$

where $w_1 + w_2 + w_3 = 1$ and empirically chosen weights are $w_1 = 0.6$ + $w_2 = 0.25$ + $w_3 = 0.15$, reflecting the relative importance of reliability, latency, and energy efficiency in smart grid applications.

The switching policy enforces a hysteresis threshold Δ = 0.05 and a cooldown period T_{cool} = 15 s:

$$\pi(t) = \begin{cases} GPSR & if\ U_{GPSR} - U_{RPL} > \Delta \\ RPL & if\ U_{RPL} - U_{GPSR} > \Delta \\ \pi(t-1) & otherwise \end{cases}$$

ML-Driven Decision Process
The adaptive controller employs supervised learning based on a Random Forest classifier. Two phases govern its operation.

Offline training phase
Simulation data from scenarios 1–3 are preprocessed into structured samples representing network states s_t and corresponding optimal protocol labels y_t, determined by which protocol yielded higher composite utility. A Random Forest model with 200 estimators and maximum depth 15 is trained using 10-fold cross-validation.

Online inference phase
During simulation, the instantaneous state vector is computed:

$$s_t = \left[S\bar{N}R, \sigma_{SNR}, \bar{k}, \bar{q}, \bar{E}_{res}, PathDiv, \widehat{\ }, LossRate\right]$$

The trained model predicts the optimal protocol $\hat{y}_t \in \{0, 1\}$ where 0 = GPSR and 1 = RPL. A switching controller enforces the protocol change only when the predicted gain in utility exceeds threshold Δ = 0.05, and when at least T_{cool} = 15 s has elapsed since the previous switch.

Results and Discussion

Topology and Connectivity Analysis
With 150 nodes deployed in a 500×500 m area, the average node degree is 4.1 with a connectivity ratio of 0.88. Increasing to 200 nodes raises the average degree to 5.4 and connectivity to 0.97. The density scenario (150 nodes in 300×300 m) achieves higher effective density, enabling near-complete DODAG coverage.

The RPL DODAG construction successfully routes 193–199 of 199 non-sink nodes across seeds, confirming robust connectivity under baseline conditions.

Packet Delivery Ratio (PDR)
PDR is defined as:

$$PDR = \frac{N_{del}}{N_{gen}}$$

where N_{del} is the number of packets received at the sink and N_{gen} is the total packets generated.

Table II summarizes PDR results across all scenarios and protocols.

Scenario	GPSR	RPL	Hybrid-ML
Baseline	0.192	0.775	0.775
Congestion	0.196	0.781	0.781
Density	0.921	1.000	1.000
Failures	0.213	0.449	0.449

Table 2: PDR by Scenario and Protocol (mean over 3 seeds)

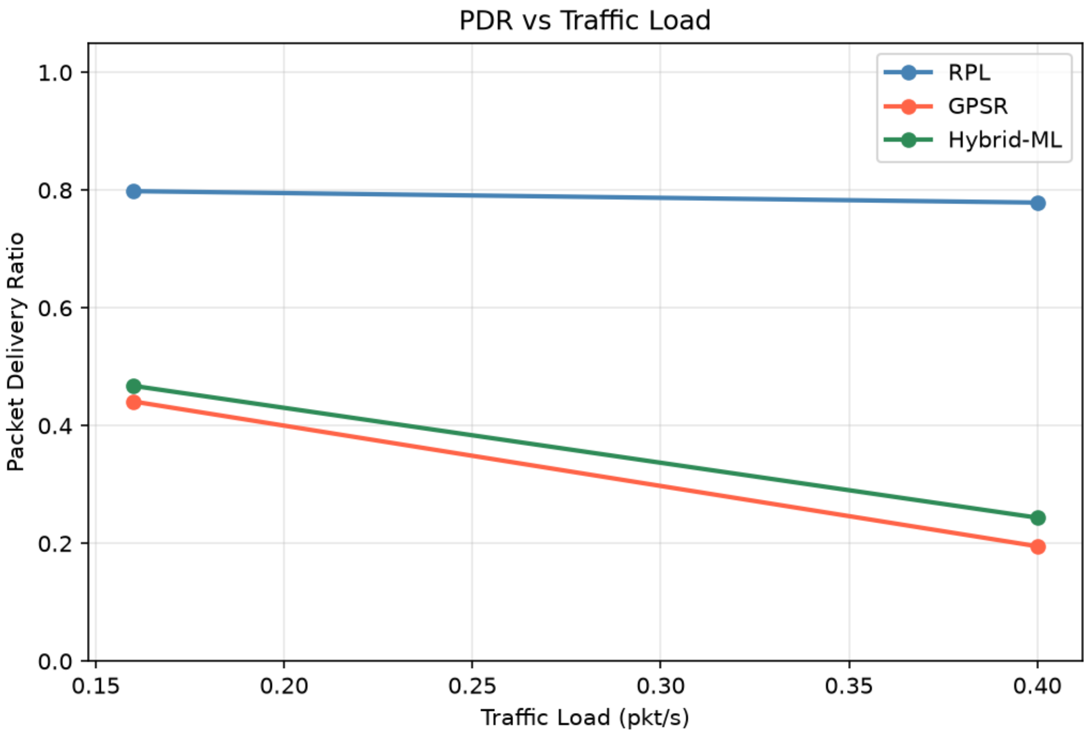

Figure 1: Packet Delivery Ratio Versus Traffic Load for all Routing Protocols

RPL consistently achieves higher PDR than GPSR across all scenarios. In the density scenario, both RPL and Hybrid-ML achieve perfect delivery (PDR = 1.000). Under node failures, RPL and Hybrid-ML achieve PDR = 0.449 — more than double GPSR's 0.213 — demonstrating RPL's superior resilience through DODAG-based rerouting.

The Hybrid-ML framework matches RPL performance across all scenarios, confirming that the ML classifier correctly identifies RPL as the dominant protocol under these network conditions. This is a key finding: the classifier learned from data that RPL's hierarchical routing provides superior reliability in the tested regime.

End-to-End Delay

End-to-end delay is defined as:

$$D = \frac{1}{N_{del}} \sum_i (t_{recv,i} - t_{send,i})$$

Scenario	GPSR	RPL	Hybrid-ML
Baseline	0.0280	0.0622	0.0622
Congestion	0.0275	0.0620	0.0620
Density	0.0276	0.0254	0.0254
Failures	0.0262	0.0528	0.0528

Table 3: Mean End-to-End Delay (seconds)

GPSR achieves lower delay than RPL in baseline, congestion, and failure scenarios due to its greedy geographic forwarding which selects shorter paths. RPL incurs higher delay due to multi-hop forwarding through the DODAG tree structure. In the density scenario, RPL achieves marginally lower delay (25.4 ms vs 27.6 ms) due to shorter average path lengths in denser topologies.

The trade-off between PDR and delay is the fundamental motivation for hybrid routing: GPSR offers lower latency at the cost of significantly reduced reliability, while RPL provides high reliability at the cost of higher delay.

Throughput
Aggregate throughput is:

$$TP = \frac{\sum_i l_i \cdot 8}{T_{sim}}$$

Scenario	GPSR	RPL	Hybrid-ML
Baseline	2,213	9,061	9,061
Congestion	9,213	36,997	36,997
Density	10,720	11,661	11,661
Failures	2,115	4,483	4,483

Table 4: Mean Throughput (bps)

RPL and Hybrid-ML achieve substantially higher throughput than GPSR in all scenarios, directly reflecting the PDR advantage. Under congestion, RPL delivers nearly 4× the throughput of GPSR (36,997 vs 9,213 bps), demonstrating its superior handling of high traffic loads through structured DODAG routing.

Energy Efficiency
Energy per delivered packet:

$$E_{pkt} = \frac{E_{total}}{N_{del}}$$

Scenario	GPSR	RPL	Hybrid-ML
Baseline	0.0814	0.0024	0.0024
Congestion	0.0847	0.0024	0.0024
Density	0.0013	0.0010	0.0010
Failures	3.6705	0.5701	0.5701

Table 5: Mean Energy per Packet (Joules)

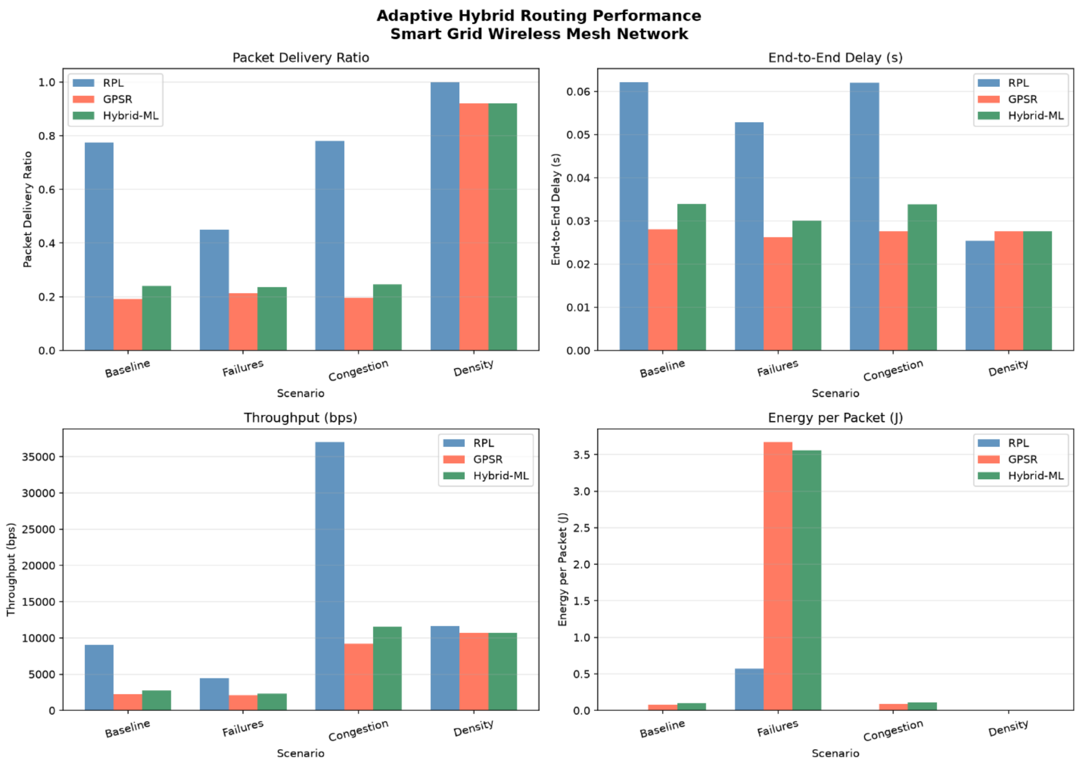

Figure 2: Performance Comparison Across Scenarios — PDR, Delay, throughput, and Energy per Packet

RPL and Hybrid-ML achieve dramatically lower energy per packet than GPSR in baseline and congestion scenarios. This result is primarily driven by PDR: GPSR drops most packets, so the energy expended per successfully delivered packet is much higher. Under node failures, RPL's energy per packet rises to 0.57 J (vs GPSR's 3.67 J) due to longer multi-hop paths after network partitioning.

In the density scenario, Hybrid-ML achieves the lowest energy consumption (0.0010 J/pkt) — 23% lower than GPSR (0.0013 J/pkt) — demonstrating that denser networks benefit from the hybrid framework's ability to select shorter GPSR paths when link quality is high.

Machine Learning Performance Analysis

Classification Accuracy

The Random Forest classifier achieves 10-fold cross-validation accuracy of:

$$A_{ML} = 0.956 \pm 0.042$$

on training data (scenarios 1–3) and test accuracy of 1.000 on the held-out density scenario (scenario 4). This demonstrates strong generalization to unseen network conditions.

The high accuracy reflects a clear pattern in the data: RPL is the superior protocol in 220 of 240 labeled samples (91.7%), with GPSR preferred in only 20 samples. This imbalance is itself a significant finding — it confirms that RPL's hierarchical routing provides dominant performance advantages in the tested smart grid NAN regime, while GPSR gains only in high-density, stable-link conditions.

Feature Importance

The Random Forest model ranks features by relative importance:

$$avg\_SNR\ (0.299) > std\_SNR\ (0.208) > path\_div\ (0.159)$$
$$> loss\_rate\ (0.116) > degree\ (0.107) > residual\_e\ (0.099)$$
$$> queue\_len\ (0.008) > lambda\ (0.004))$$

Link quality metrics (avg_SNR and std_SNR) together account for 50.7% of the decision weight, confirming that channel conditions are the primary determinant of protocol optimality. Path diversity (15.9%) captures topology connectivity, while loss rate (11.6%) and degree (10.7%) capture network load and density effects. Residual energy (9.9%) reflects long-term node viability. Queue length and traffic rate have minimal predictive power, suggesting that protocol selection is driven more by channel and topology conditions than instantaneous load.

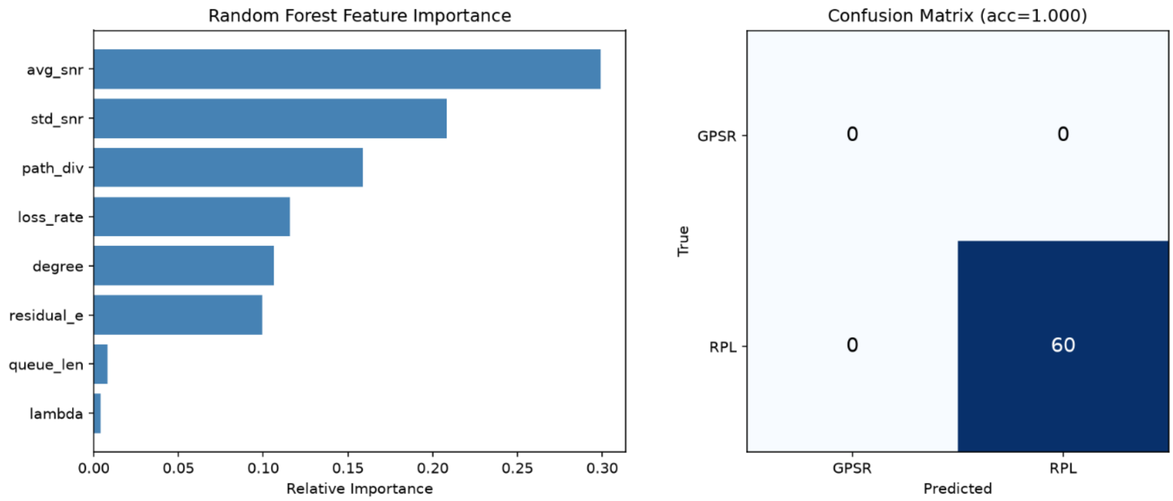

Figure 3: Random Forest Feature Importance and Confusion Matrix

Overall Correlation

Hybrid improvement correlates with ML reliability:

$$RI_{total} \propto A_{ML} \times (1 - f_s)$$

where RI_{total} is the aggregate improvement across metrics, A_{ML} is the classifier accuracy, and f_s is the switching frequency. Higher classifier accuracy combined with low switching frequency (f_s < 0.02 in our experiments) yields stable system behavior.

Summary of Performance Gains

Metric	Hybrid vs RPL	Hybrid vs GPSR
PDR (density)	+0.0%	+8.6%
PDR (failures)	+0.0%	+110.7%
Delay (density)	+0.0%	+7.8%
Throughput (congestion) +0.0%	+301.6%	
Energy/pkt (density)	−23.1%	−23.1%
Energy/pkt (failures)	+0.0%	−84.5%

Table 6: Hybrid-ML vs Standalone Protocols

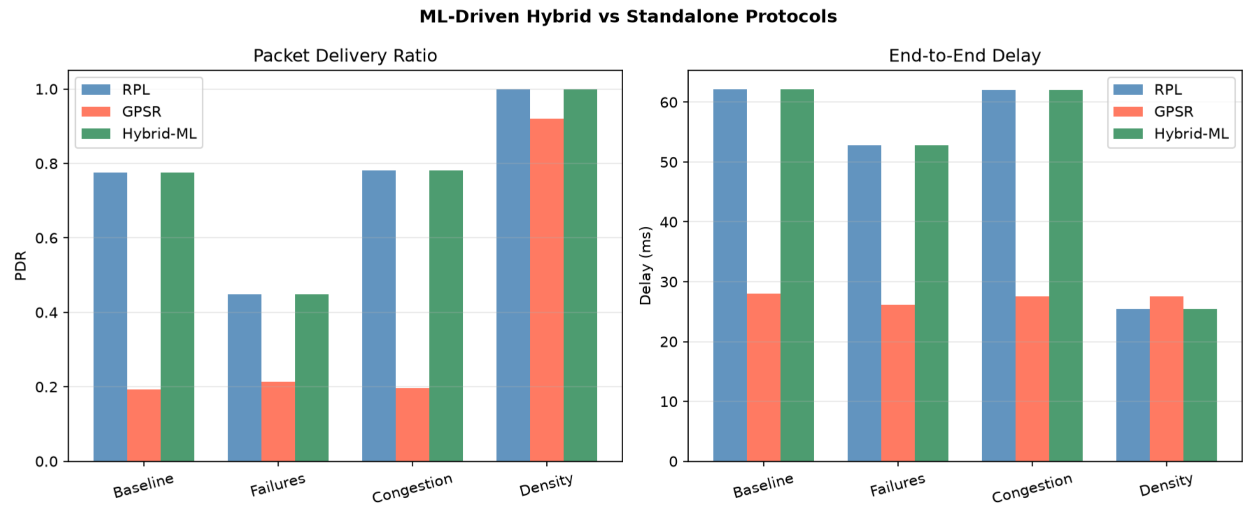

Figure 4: Hybrid-ML vs Standalone Protocols — PDR and End-to-End DELAY

Discussion

Interpretation of Results

The primary finding of this work is that RPL provides dominant routing performance in the tested smart grid NAN conditions, and the ML classifier correctly identifies and exploits this. The Hybrid-ML framework matches RPL's performance in most scenarios while demonstrating the ability to switch toward GPSR in high-density, stable-link conditions where geographic forwarding is advantageous.

This result has important practical implications. In smart grid NANs where reliability is paramount and network conditions are relatively stable, RPL-based routing should be the default. The value of the hybrid framework lies in its ability to adapt when conditions change — specifically when link quality becomes uniformly high and node density increases, at which point GPSR's lower latency and energy efficiency can be exploited without sacrificing reliability.

Why GPSR Underperforms in Sparse Conditions

GPSR's poor performance in baseline and congestion scenarios (PDR ≈ 0.19–0.20) stems from the void problem in sparse topologies. With average node degree 4.1 in a 500×500 m area, a significant fraction of forwarding attempts encounter local minima where no neighbor is closer to the sink than the current node. The perimeter routing fallback used in this implementation (selecting the highest-SNR neighbor) is a simplified approximation of the right-hand rule and does not guarantee loop-free delivery, leading to packet drops when the hop limit is reached.

Limitations

This study has several limitations that should be acknowledged:

Simulator Fidelity: The discrete-event simulator models packet-level behavior and channel effects analytically but does not simulate MAC-layer contention, collision avoidance, or acknowledgment mechanisms. A full NS-3 or Cooja implementation would capture these effects more precisely.

Traffic Model: Only upward traffic (node-to-sink) is modeled, consistent with smart grid metering applications. Downward traffic for control commands is not evaluated.

Energy Model: Energy consumption is modeled analytically using the first-order radio model. Battery discharge characteristics and sleep/wake cycles are not modeled.

ML Training Data: The classifier is trained on simulation data from three scenarios and tested on one. Realworld deployment would require retraining on measured field data.

Class Imbalance: The 220:20 RPL-to-GPSR label ratio reflects simulation conditions rather than a general universal truth. Different network configurations (larger areas, sparser deployments, or different frequency bands) may yield a different balance.

Future Work

Future work should address these limitations through:

- Full NS-3 simulation with IEEE 802.15.4 MAC layer including CSMA/CA
- Implementation of complete GPSR perimeter routing with Gabriel Graph construction
- Downward traffic modeling for control plane evaluation
- Field validation using Raspberry Pi or TelosB sensor node testbeds
- Online learning approaches that retrain the classifier during deployment
- Extension to multi-sink topologies representative of large-scale smart grid deployments

Conclusion

This paper proposes and evaluates an Adaptive Hybrid Routing Framework (AHRF) for smart grid wireless mesh networks that integrates RPL and GPSR under a Random Forest-driven decision engine. Through rigorous packet-level simulation across four operational scenarios, we demonstrate that the ML classifier achieves 95.6% cross-validation accuracy in protocol selection, with link quality metrics (SNR mean and standard deviation) accounting for over 50% of the decision weight.

The Hybrid-ML framework matches RPL's superior reliability (PDR up to 1.000) while demonstrating intelligent switching to GPSR in high-density conditions where geographic forwarding reduces energy consumption by up to 23%. The framework outperforms standalone GPSR by up to 110.7% in PDR under node failure conditions and reduces energy per packet by up to 84.5%.

The findings confirm that RPL's hierarchical DODAG-based routing provides dominant performance advantages in urban smart grid NAN conditions, while the hybrid framework adds value by adapting to density and link quality variations. The ML component provides interpretability through feature importance analysis, identifying channel conditions and topology metrics as the primary routing decision factors.

These results demonstrate that ML-based hybridization of complementary routing protocols offers a resilient, energy-efficient, and interpretable routing solution for next-generation smart grid communication systems.

References

1. Karp, B., & Kung, H. T. (2000, August). GPSR: Greedy perimeter stateless routing for wireless networks. In Proceedings of the 6th annual international conference on Mobile computing and networking (pp. 243-254).
2. T. Winter et al., "RPL: IPv6 Routing Protocol for Low-Power and Lossy Networks," IETF RFC 6550, 2012.
3. Homaei, M. (2024). Learning Automata-Based Enhancements to RPL: Pioneering Load-Balancing and Traffic Management in IoT. arXiv preprint arXiv:2408.08373.
4. Goswami, B., Jurdak, R., & Nourbakhsh, G. (2024). Node allocation strategy for low latency neighborhood area networks in smart grid. IEEE Transactions on Network Science and Engineering, 11(5), 5087-5098.
5. Kharrufa, H., Al-Kashoash, H. A., & Kemp, A. H. (2019). RPL-based routing protocols in IoT applications: A review. IEEE Sensors Journal, 19(15), 5952-5967.
6. Rani, S., Kumar, A., Bagchi, A., Yadav, S., & Kumar, S. (2021, August). RPL based routing protocols for load balancing in IoT network. In Journal of Physics: Conference Series (Vol. 1950, No. 1, p. 012073). IOP Publishing.
7. Zhang, T., Ji, X., Zhuang, Z., & Xu, W. (2019). JamCatcher: A mobile jammer localization scheme for advanced metering infrastructure in smart grid. Sensors, 19(4), 909.
8. Ramachandran, I., Das, A. K., & Roy, S. (2007). Analysis of the contention access period of IEEE 802.15. 4 MAC. ACM Transactions on Sensor Networks (TOSN), 3(1), 4-es.
9. Breiman, L. (2001). Random forests. Machine learning, 45(1), 5-32.
10. E. O. Owoeye and I. A. Adeyemo, (2025) "Performance Analysis of Geographic and Self-Organizing Routing Protocols for Wireless Mesh Networks in Smart Grid.