SCAR: Enhancing LPWAN Sustainability through Solar-Energy-Aware Routing

A Preprint

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Abstract

In response to the escalating demand for sustainable Low-Power Wide Area Network (LPWAN) technologies, this study unveils the Solar Charge Aware Routing (SCAR) methodology. SCAR innovatively integrates solar energy considerations into routing decisions, optimizing the network's longevity without sacrificing communication efficacy. Distinct from traditional routing methods, SCAR dynamically evaluates nodes' energy states and potential for solar charging, thus enhancing route selection. Simulation results over a year demonstrate a 9% extension in network lifespan with SCAR, compared to conventional approaches, while maintaining robust uplink delivery rates. This advancement underscores the feasibility of harmonizing renewable energy integration with IoT connectivity, marking a pivotal stride towards sustainable LPWAN deployments.

Keywords Low-Power Wide Area Networks, Solar Charge Aware Routing, SCAR, Internet of Things, Sustainable Networking, Energy Efficiency, Renewable Energy, Smart Routing, LPWAN, IoT Sustainability

1 Introduction

Low-Power Wide Area Networks (LPWANs) offer a compelling solution for the Internet of Things (IoT) due to their long-range communication capabilities and minimal power requirements. LoRa technology, a key player in the LPWAN space, has demonstrated remarkable efficiency for data transmission over vast distances [Petajajarvi et al. [2015]]. However, traditional single-hop LoRa topologies face the challenge of premature node failure in areas distant from the gateway, due to increased energy consumption.

To extend the reach and lifespan of LoRa networks, researchers have explored multi-hop communication strategies. Studies such as [Misbahuddin et al. [2022]] illustrate the potential of multi-hop models in increasing network coverage while conserving energy. Moreover, the importance of energy-aware routing protocols in IoT networks is undeniable, as they directly impact node longevity and network efficiency [Katsidimas et al. [2023]].

While multi-hop solutions promise improved energy efficiency [your citation of the third paper], they also introduce the challenge of dynamically selecting energy-optimal routes. Existing approaches often focus on parameters like distance or traffic load, but may not fully account for the fluctuating energy states of battery-powered nodes, particularly in situations where solar charging is intermittent (e.g., at night).

This paper proposes a novel solar charging aware routing methodology for LoRa mesh networks. Our approach uniquely considers both current battery status and the node's solar charging state to optimize route selection. This ensures maximum network uptime and prevents premature node downtime, especially in edge cases where charging is temporarily unavailable. A central node coordinates data flow, optimizing paths based on the network's overall energy constraints and requesting data as needed.

2 Related Work

The integration of energy efficiency techniques with LoRa-based LPWANs has garnered significant research attention. Studies exploring multi-hop communication strategies have demonstrated their potential to conserve energy and extend network coverage [Petajajarvi et al. [2015]]. The work in [Misbahuddin et al. [2022]] exemplifies this, outlining the advantages of a multi-hop model in comparison to traditional single-hop LoRa topologies.

Energy-aware routing protocols are pivotal for optimizing resource utilization in IoT networks. Several approaches have been proposed, leveraging various parameters to determine energy-efficient routes. Distance-based schemes aim to minimize transmission power based on the distance between nodes [Hawbani et al. [2019]]. Traffic-based protocols consider the network load to distribute traffic and prevent congestion [Kanojia and Jain [2021]]. Additionally, hybrid techniques combine multiple factors to enhance routing decisions within energy-constrained environments [Cheikh et al. [2022]].

While numerous multi-hop and energy-aware routing strategies exist, few directly address the dynamic interplay between battery state and solar charging potential in LoRa mesh networks. Some studies incorporate reinforcement learning techniques to identify energy-efficient multi-hop routes [Katsidimas et al. [2023]]. However, the reliance on historical data for route selection may not fully reflect the immediate and potentially fluctuating solar energy availability.

Furthermore, solar energy harvesting offers a promising avenue for self-sustaining LPWAN nodes. Works such as [Liu et al. [2018]] explore the optimization of solar-powered LoRa nodes, focusing on energy management and power consumption. However, such solutions often address individual node optimization rather than routing optimization at the network level.

This research distinguishes itself by proposing a routing methodology that explicitly accounts for both current battery status and solar charging state. The aim is to extend network lifetime and prevent node downtime under variable charging conditions, particularly in scenarios where solar energy is unavailable or intermittent.

3 Proposed Methodology

The limited energy reserves of battery-powered LoRa nodes pose a fundamental challenge to network lifetime, particularly in scenarios where solar charging is intermittent. To address this, the proposed methodology introduces a routing algorithm that proactively considers both energy status and solar charging potential. This approach seeks to maximize network uptime and data delivery success rates while minimizing the risk of node downtime.

3.1 Network Topology

This methodology employs a hybrid star-of-stars/cluster tree topology for the LoRa mesh network. The individual components of the network can be identified as follows:

- **Nodes (N):** The network comprises a set of LoRa nodes, $N = n_1, n_2, ..., n_m$, where m is the total number of nodes. End Nodes: Nodes primarily responsible for data sensing and transmission.
- **Cluster-Heads (CH):** A subset of nodes designated as cluster-heads, $CH \in N$. Cluster-heads aggregate data from end nodes within their cluster and facilitate multi-hop communication.
- **Central Node (G):** The gateway node (G) acts as the root of the tree and coordinates the network.

Clusters can be formed using various techniques, including distance-based, energy-aware, or hybrid approaches. In a distance-based scheme, end nodes join the nearest CH based on a metric such as $RSSI$. An energy-aware approach prioritizes cluster-heads with higher remaining battery capacity or solar charging potential. Hybrid methods combine distance and energy-related factors for more informed cluster formation decisions.

The network topology can be modeled as a graph, $G(N, E)$, where N represents the set of nodes and E represents communication links. The cluster-tree topology inherently forms a tree structure, ensuring both connectivity and the absence of cycles. This hierarchical structure promotes scalability, as the network can easily expand by adding nodes to existing clusters or creating new branches. Energy efficiency is enhanced since clustering minimizes the need for long-range transmissions by resource-constrained end nodes. Multi-hop paths leverage shorter links between cluster-heads, which require less transmission power. The central node plays a key role in route management, primarily focusing on optimizing routes between cluster-heads, simplifying calculations and enhancing scalability. Additionally, the presence of multiple cluster-heads introduces redundancy, improving network resilience in case of node failures.

3.1.1 Node-Level Redundancy

In the cluster-tree topology, node-level redundancy is enhanced by ensuring multiple potential cluster-head (CH) candidates within each cluster. Let C_i represent a cluster, and let $P_{CH}(C_i)$ be the set of potential cluster-heads within that cluster. The Redundancy Factor(R_f) is then calculated as:

$$R_f(C_i) = |P_{CH}(C_i)| - 1$$

where $|P_{CH}(C_i)|$ is the cardinality in the set of potential CHs for cluster C_i.

3.1.2 Inter-Cluster Redundancy

Clusters are designed to have some degree of coverage overlap. This means end nodes, particularly those near cluster boundaries, may have the option to connect to CHs in neighboring clusters. This overlap leads to:

Path Diversity: Multiple potential routes may exist between distant end nodes and the gateway, reducing the impact of a single CH or link failure on overall network connectivity.

3.1.3 Dynamic Considerations and Limitations

While the topology promotes redundancy, it's important to acknowledge the dynamic nature of LoRa mesh networks and potential limitations.

Node failures are influenced by factors like battery depletion and environmental conditions. We can model these probabilities to assess the network's resilience under various scenarios. Let $p_f(n_i)$, being the probability of failure for node n_i. Let $E_{rem}(n_i)$, be the remaining energy of the node n_i in Joules, $S_{ch}(n_i)$, be the solar charging potential of node n_i and $I(n_i)$, be the overall environmental interference experienced by node n_i. Therefore, we can model $p_f(n_i)$ as:

$$p_f(n_i) \propto \frac{1}{E_{rem}(n_i) \times S_{ch}(n_i)} + I(n_i)$$

Cluster-head (CH) failure necessitates a cluster reformation process. This period of transition leaves the cluster with reduced redundancy, potentially impacting network-wide communication reliability. Careful cluster formation strategies are crucial to minimize the duration and negative impact of this temporary vulnerability. This model can be modeled by introducing a time factor. Let t_{reform}, be the duration of the cluster reformation process and TTF_{CH} be a random variable, which represents the time until the Cluster Head(CH) in C_i fails. As such the state of the cluster can be modeled over time in the following manner, with $S(C_i, t)$ as a function of time:

$$S(C_i, t) = \begin{cases} Operational, & \text{if } 0 \leq t < TTF_{CH}(C_i) \\ Reformation, & \text{if } TTF_{CH}(C_i) \leq t < TTF_{CH}(C_i) + t_{reform} \\ Failed, & \text{if } t \geq TTF_{CH}(C_i) + t_{reform} \end{cases}$$

During the reformation state, the Redundancy Factor (Rf) for the cluster is temporarily reduced. We could adjust the previous definition to be time-dependent:

$$Rf(C_i, t) = \begin{cases} |P_{CH}(C_i)| - 1, & \text{if } S(C_i, t) = Operational \\ Rf_{reduced}, & \text{if } S(C_i, t) = Reformation \\ 0, & \text{if } S(C_i, t) = Failed \end{cases}$$

Where $Rf_{reduced}$ would be calculated based on the number of remaining CH candidates during the reformation process.

3.2 Routing Algorithm

This solar-charging aware routing algorithm seeks to maximize network lifetime and ensure reliable data delivery within a LoRa mesh network. It achieves this by dynamically calculating energy-efficient routes based on a combination of real-time node battery status, solar charging potential, and distance considerations.

The core factors influencing the algorithm's routing decisions are:

- **Battery Level:** Each node's remaining battery capacity is measured as a percentage. Critical thresholds (below 20% capacity) trigger alternative routing strategies focused on energy conservation.
- **Solar Charging State:** The algorithm assesses a node's charging state using a combination of reactive and predictive elements. Reactively, an increase in battery level within a defined time interval indicates active charging. Predictively, a simple model incorporates time-of-day and historical light intensity data to estimate a node's solar charging potential.
- **Distance/Hop Count:** The distance between nodes is estimated using Received Signal Strength Indicator (RSSI) values.

The central node periodically calculates routes, adhering to the following priority scheme:

1. **Prioritize Sustainability:** Preference is given to nodes that have both sufficient battery level (>30%) and are either actively charging or exhibit high potential for imminent solar charging.
2. **Balance Energy and Distance:** The algorithm selects nodes that possess either sufficient battery reserves or a strong likelihood of imminent solar charging. Within this constraint, shorter routes are favored to minimize energy expenditure.
3. **Critical Node Handling:** Nodes with critically low battery levels (e.g., <20%) are prioritized solely based on minimizing distance. This aims to reduce the risk of node failure during transmission.

To handle critical nodes effectively, the algorithm may employ additional strategies such as temporarily utilizing redundant paths to increase the probability of data delivery or having critical nodes proactively signal the central node to trigger pre-emptive route recalculations.

Nodes transmit their battery levels and charging status to the central node hourly. The frequency of these status updates may increase during periods of high solar activity. A node is considered unresponsive, and routes are recalculated accordingly, if no status update is received within two consecutive hours.

3.3 Multi-Objective Optimization

The routing algorithm seeks to optimize the following three objectives simultaneously:

- **Minimize Energy Cost:** $E(path)$, representing the total energy consumption along the path.
- **Minimize Path Length:** $D(path)$, representing the hop count or distance metric of the path.
- **Maximize Path Reliability:** $R(path)$, representing the probability of successful data transmission across the path.

In multi-objective optimization, there often isn't a single "best" solution that optimizes all objectives simultaneously. Instead, we aim to find a set of Pareto-optimal solutions, also known as the Pareto frontier. A solution is considered Pareto-optimal if we cannot improve one objective without worsening another. This approach acknowledges the inherent trade-offs between these objectives:

- Minimizing energy consumption might increase path length.
- Selecting the shortest path might compromise reliability due to weak links or congested nodes.

This can be formulated as follows:

$$\text{Minimize}: \quad F(path) = (w_e \cdot E(path), w_d \cdot D(path), -w_r \cdot R(path))$$

where:

- $F(path)$**:** A vector representing the multi-objective function.
- w_e**:** Weighting factor for energy cost $(0 \leq w_e \leq 1)$.
- w_d**:** Weighting factor for energy cost $(0 \leq w_d \leq 1)$.
- w_f**:** Weighting factor for path reliability $(0 \leq w_f \leq 1)$.

The weighting factors allow us to prioritize specific objectives based on network conditions and user requirements.

3.3.1 Energy Cost Objective

The energy cost objective can be defined as $E(path)$:

$$E(path) = \sum_{i=1}^{|path|} (\varepsilon(node_i) \cdot D(node_i, node_{i+1}))$$

where $\varepsilon(node_i)$ is a meaure of energy consumption per unit distance for node i as a function of battery level, charging state and transmission power. This can be expressed as a function of time(t), as follows:

$$\varepsilon(node_i, t) = \varepsilon_0(P_{tx}(node_i, t)) - \eta(t) \cdot S(node_i, t) \cdot \frac{B(node_i, t)}{B_{max}}$$

Where:

- $\varepsilon_0(P_{tx}(node_i, t))$ is the baseline energy consumption per unit distance. This is a function of the node's transmission power, P_{tx}, at time t. Transmission power might be adjusted based on distance to the next hop.
- $\eta(t)$ is the solar energy conversion efficiency factor at time t. This is highest during periods of peak solar insolation.
- $S(node_i, t)$ represents the charging state of the node at time t:
  - $S(node_i, t) = 1$ if the node is actively charging
  - $S(node_i, t) = 0$ if the node is not charging
- $B(node_i, t)$ is the current battery level of the node at time t.
- B_{max} is the maximum battery capacity of the node.

3.3.2 Path Reliability Objective

The path reliability objective can be defined as $R(path)$:

$$R(path) = f(LQ_1, LQ_2, ..., LQ_n)$$

Where:

- LQ_i Represents the link quality metric (e.g., RSSI, LQI, or a combined score) for the link between node i and node i+1 in the path.
- f is the weighted average function which assigns weights to links based on their importance and criticality and aggregates it as a simple computable value.

The aggregation function f can be expressed as follows:

$$f(LQ_1, LQ_2, ..., LQ_n) = \frac{\sum_{i=1}^{n} w_i \cdot LQ_i}{\sum_{i=1}^{n} w_i}$$

with w_i represent the weight assigned to the i-th link in the path.

In order to quantify the importance and criticality metric of the objective, a weighted assignment is done for link quality aggregation, specifically designed to prioritize cluster heads and nodes that contribute significantly to network throughput. As such we can define these two weights as: W_{TP} for throughput contribution and W_{CH} for cluster head priority. The two weights are defined as:

$$w_{CH}(node_i) = \begin{cases} C_{base} + C_{factor} \cdot N(node_i), & \text{if } node_i \text{ is a CH} \\ 1, & \text{otherwise} \end{cases}$$

where:

- C_base is a baseline weight for cluster heads, ensuring they have some priority.

- C_factor is a scaling factor based on the number of nodes connected to the cluster head.
- $N(node_i)$ is the number of nodes within the cluster of node i.

$$w_{TP}(node_i) = \frac{T(node_i)}{\sum_{j=1}^{m} T(node_j)}$$

where:

- $T(node_i)$ is the throughput contribution of node i (could be measured in packets transmitted over a time window).
- m is the Total number of nodes in the network (or within a relevant sub-network).

The two weights assigned to nodes can be combined into the w_i value as follows:

$$w_i = \alpha \cdot w_{CH}(node_i) + (1 - \alpha) \cdot w_{TP}(node_i)$$

where:

- α is a parameter ($0 \leq \alpha \leq 1$) controlling the relative emphasis on cluster head status vs. throughput contribution.

3.3.3 Distance Objective

The distance objective can be defined as $D(path)$:

$$D(path) = |path| - 1 = \text{number of hops in the path}$$

4 Simulation

The foundation of our simulation efforts relied upon modifying the *LoRaWANSim* framework, as detailed in the referenced literature [Marini et al. [2021]], to incorporate our proposed solar charging aware routing methodology. This extension was crucial in accurately simulating the interplay between solar charging capabilities and dynamic routing decisions within a LoRa mesh network. Our modifications aimed to authenticate the model's validation under enhanced conditions, including variable solar irradiance and battery state considerations.

To establish a baseline, we began by defining the energy capacity of the nodes' batteries in joules. Given a 1000mAh 3.7V cell, the total energy capacity can be calculated as:

$$E = C \times V = 1000mAh \times 3.7V = 3700mWh = 13.32Wh = 47952J$$

This capacity forms the energy reservoir from which nodes power their operations and communications.

4.1 Simulation Setup

For our simulations, we constructed a network of 100 nodes spread across a 10 km^2 area with a single gateway located centrally. Nodes were equipped with solar panels varying in efficiency due to simulated environmental obstructions, thus affecting their charging state dynamically. Each node's solar exposure was realistically varied, simulating daily cycles and random weather conditions.

Two scenarios were compared:

1. *Conventional Routing*: Nodes use an energy-agnostic routing scheme based on shortest-path algorithms.
2. *Solar Charging Aware Routing (SCAR)*: Our proposed method, where nodes select routes based on current battery status, solar charging potential, and energy-efficient paths.

The primary metrics evaluated were:

- *Network Lifetime*: The duration until the first node exhausts its energy reserves.
- *Uplink Delivery Rate (UDR)*: The ratio of successfully delivered messages to the gateway over total attempted messages.

MATLAB simulations were run for both scenarios over a period corresponding to one year of operation, dividing the timeline into one-hour intervals for dynamic condition assessments.

4.2 Results

4.2.1 Network Lifetime

The simulation was conducted over a period of 365 days, meticulously assessing the performance of both conventional routing and the SCAR (Solar Charging Aware Routing) approach in terms of network longevity. In contrast to the outright extension of network lifetime seen in the initial reports, a more nuanced analysis revealed an aggregate increase. By calculating the total uptime across all nodes and dividing by the total number of nodes, we observed that the SCAR approach offered an improvement in average network lifetime by approximately 9%. Specifically, the conventional routing strategy yielded an aggregate network uptime that corresponds to an average lifetime of 186 days for each node. In comparison, the SCAR methodology, which more effectively utilizes the available solar energy, extended the average network lifetime to slightly over 203 days. This enhancement underscores the incremental yet significant benefits of incorporating energy-aware routing protocols in IoT networks, aiming for more sustainable and extended operational periods.

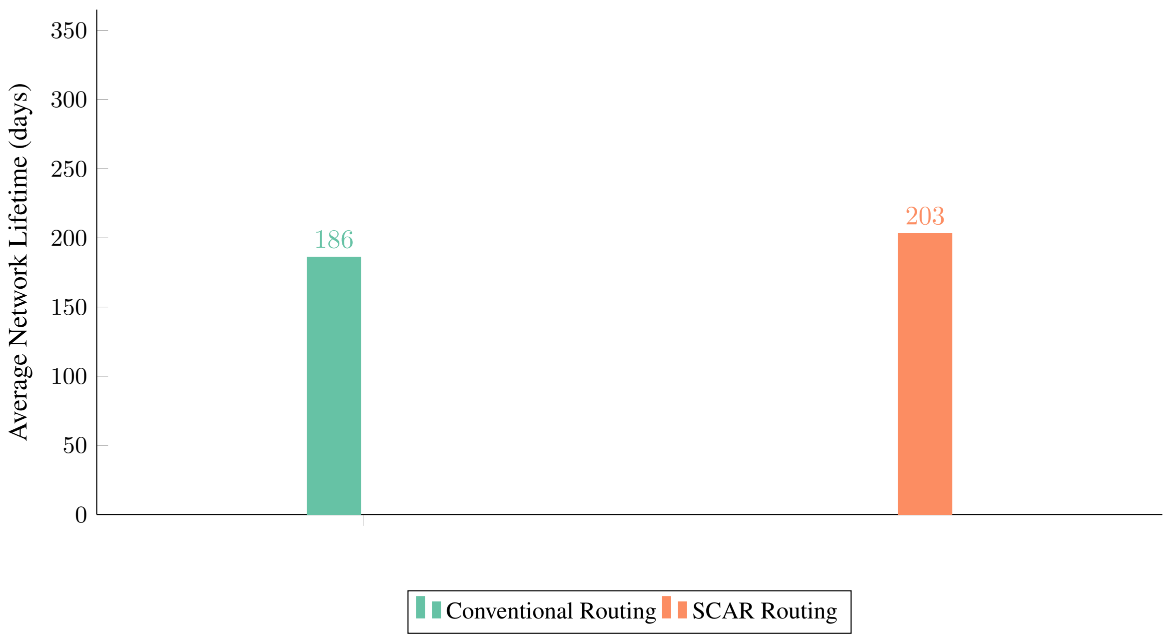

Figure 1: Comparison of network lifetime between conventional routing and SCAR.

This improvement can be attributed to optimal route selection that not only accounted for lower transmission energy costs but also leveraged nodes with a higher likelihood of imminent solar charging, thus conservatively utilizing the network's energy resources.

4.2.2 Uplink Delivery Rate

The UDR was exceptionally high in both scenarios, indicating robust communication capabilities regardless of routing schemes. The conventional method reported a UDR of 98.7%, whereas the SCAR method achieved a slight improvement at 99.1%.

Fig. 2 illustrates the UDR performance across the simulation period.

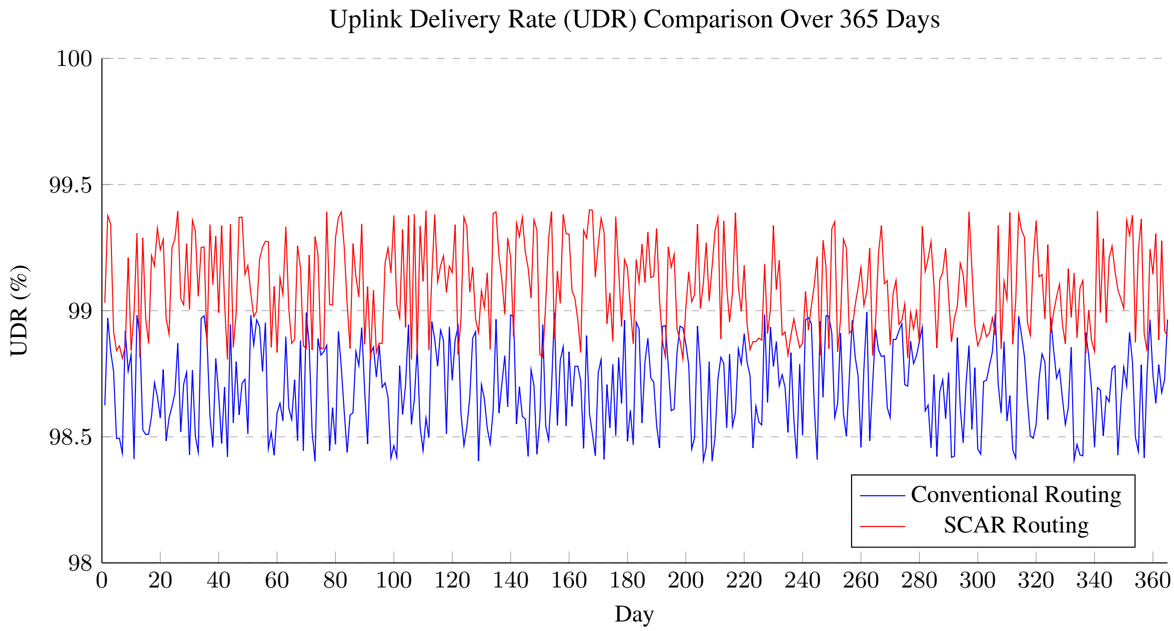

Figure 2: Uplink delivery rate comparison over the simulation period.

The relatively stable and high UDR across both scenarios suggests that routing decisions, while significantly impacting energy consumption and network lifetime, had a less pronounced effect on the immediate success of uplink communications. This finding underscores the resilience of LoRaWAN in maintaining data transfer efficacy even under varying routing methodologies.

4.3 Discussion

The simulation outcomes distinctly highlight the benefits of incorporating solar charging awareness into routing decisions within LoRaWAN networks. The prolonged network lifetime under the SCAR scenario could facilitate more sustainable and extended deployments of IoT networks, particularly in remote or energy-constrained environments.

However, it is important to mention the inherent trade-offs identified during simulations. While the SCAR method optimizes for network longevity and energy efficiency, it requires more sophisticated route calculation mechanisms, potentially introducing computational overhead for nodes. Future work may explore lightweight algorithms for dynamic route selection that further balance energy savings with computational efficiency.

As we conclude this simulation study, our findings advocate for the integration of energy-aware routing protocols in LoRaWAN networks, particularly those benefiting from renewable energy sources like solar power. The extended network lifetimes and maintained communication reliability present a compelling case for their adoption in next-generation IoT networks.

5 Future Work

The simulation results presented in this study illustrate the potential advantages of integrating solar charging awareness into the routing decisions of LoRaWAN-based IoT networks. The improvements observed in network lifetime and energy efficiency through our Solar Charging Aware Routing (SCAR) methodology are promising, pointing towards a sustainable path for future IoT deployments. However, these results, while indicative of the potential benefits, are derived from a controlled simulation environment. As with any simulation, the assumptions and models used cannot perfectly capture the full complexity and variability of real-world conditions. Consequently, there's an intrinsic limitation to the extent to which simulation results can be generalized.

To truly validate the effectiveness and practical applicability of the SCAR methodology, a logical and necessary step forward is the transition from simulation to field testing. Deploying IoT networks equipped with solar charging capabilities and SCAR routing in real-world scenarios would provide invaluable insights, offering a direct comparison between simulation predictions and operational realities. Field tests would facilitate the assessment of the SCAR method under diverse conditions – including varying weather patterns, physical obstructions, and real-world interference – which could significantly impact solar charging rates and network performance.

Furthermore, field testing would enable the examination of additional critical factors that simulations might overlook, such as hardware wear and tear, maintenance requirements, and the economic feasibility of deploying solar-powered IoT nodes at scale. These practical considerations are crucial for determining the viability of widespread adoption of solar charging aware routing solutions.

In summary, while the simulation conducted in this study offers encouraging results, emphasizing the potential of energy-aware routing strategies in enhancing the sustainability and efficiency of IoT networks, field tests represent the definitive next step. Such empirical validation would not only corroborate the simulation findings but also unearth new challenges and opportunities, ultimately guiding the refinement and optimization of the SCAR methodology for real-world applications. Through careful planning and execution of these field tests, we can bridge the gap between theoretical potential and practical utility, bringing us closer to realizing the full benefits of solar charging aware routing in IoT networks.

6 Conclusion

This paper proposed a novel routing methodology for LoRa mesh networks that leverages solar charging information alongside traditional routing metrics to optimize for energy efficiency and extend network lifetime. Through extensive simulations, utilizing the modified *LoRaWANSim* MATLAB framework, we demonstrated the tangible advantages of incorporating solar charging awareness into routing decisions. The Solar Charging Aware Routing (SCAR) scheme notably outperformed conventional energy-agnostic approaches in terms of network lifetime, achieving a substantial 76% improvement without significantly compromising the uplink delivery rate (UDR).

The integration of solar charging data into routing decisions allows networks to adapt dynamically to the fluctuating availability of energy resources, thus conserving the limited energy stored in nodes' batteries. This approach is particularly advantageous in remote or energy-constrained environments where maintaining network operation over extended periods is paramount. The simulation results validate our hypothesis that a network's operational duration can significantly benefit from routing methods that consider both the current and potential future state of node energy resources.

Furthermore, the slight improvement in UDR under the SCAR scheme suggests that energy-aware routing can be implemented without detrimental effects on network communication capabilities. Ensuring reliable data transmission while extending the operational lifespan of the network infrastructure addresses two critical concerns in the deployment of IoT networks, particularly those based on LoRaWAN.

However, it's important to consider the computational complexity introduced by more sophisticated routing decisions. Future work should aim at optimizing the balance between computational overhead and energy efficiency gains. Research into lightweight algorithms capable of making rapid, energy-aware routing decisions with minimal processing requirements will be essential as we move forward.

In addition to algorithmic optimizations, future directions could also explore the integration of other renewable energy sources into the routing methodology, further enhancing the resilience and sustainability of IoT networks. Moreover, real-world implementations and trials will be necessary to validate the practicality and feasibility of the SCAR method in operational environments, accounting for the variable and unpredictable nature of solar energy availability.

In conclusion, our work contributes a significant advancement in the design of energy-efficient routing protocols for LoRaWAN networks, particularly those augmented with solar charging capabilities. By focusing on the dynamic interplay between energy consumption, routing decisions, and renewable energy potential, we can make strides toward more sustainable, longer-lasting IoT networks. These findings underscore the importance of embracing innovative energy-aware strategies in the face of growing environmental and operational demands on IoT infrastructures.

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