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A recurrent network technique for energy optimization in 6G networks with dynamic device-to-device communication

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ABSTRACT

Energy efficiency has become a paramount concern in the design and deployment of 6G networks, driven by the exponential growth of connected devices and increasing traffic demands. For domain experts grappling with dynamic device-to-device (D2D) communication scenarios, optimizing energy consumption while maintaining reliable connectivity poses a significant challenge. To address this issue, we propose a novel recurrent network technique that dynamically configures D2D communication patterns, adaptively allocating temporary base stations among network nodes to enable efficient data transmission while minimizing energy expenditure. Our simulations demonstrate substantial energy savings, extended node lifetimes, and reliable performance, with a 37% reduction in overall network energy consumption and a 65% increase in average node lifetime compared to traditional cellular communication scenarios. In conclusion, this innovative approach paves the way for sustainable and energy efficient 6G communication systems, benefiting society by reducing operational costs, minimizing environmental impact, and prolonging the usability of mobile devices.

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1. INTRODUCTION

With the advent of 6G networks, the demand for high-speed, low latency, and energy efficient communication systems has become paramount [1]. As the number of connected devices continues to grow exponentially, traditional cellular networks face significant challenges in meeting the increasing traffic demands while maintaining optimal energy consumption levels [2]. One promising solution to address this issue lies in the exploration of device-to-device (D2D) communication, which enables direct communication between nearby devices without relying solely on the base station infrastructure [3].

Traditional cellular networks often suffer from inefficient resource utilization, leading to increased energy consumption and network congestion [4]. As the density of connected devices rises, managing the energy efficiency of these networks becomes increasingly complex [5]. The integration of D2D communication can offer a viable alternative by allowing devices in close proximity to exchange data directly, bypassing the base station and reducing the overall traffic load on the network infrastructure [6]. However, the successful implementation of D2D communication requires careful consideration of factors such as network topology, device mobility, and energy constraints [7]. The literature highlights the importance of D2D communication as a crucial component for enhancing network throughput, capacity, and reducing traffic load on evolved Node B (eNB) [8]. Several studies have focused on optimizing energy efficiency in D2D communications to promote sustainable smart city development [9]. The integration of green communication techniques into smart city infrastructure is essential for achieving energy-efficient D2D communications [10].

Dong *et al.* [11] utilized RNNs to predict network traffic patterns, enabling dynamic adjustment of power levels in base stations. Ashwin *et al.* [12] explored the application of RNNs in predicting user mobility patterns to proactively manage resources and optimize energy consumption. Rau *et al.* [13] demonstrated how accurate traffic forecasting can lead to significant energy savings and improved network performance, highlighting the effectiveness of machine learning in optimizing network operations. Additionally, the utilization of D2D communication can lead to improved quality of service (QoS) performance through centralized interference mitigation algorithms [14]. Despite these advancements, the successful implementation of D2D communication requires careful consideration of factors such as network topology, device mobility, and energy constraints [15]. Existing methods often fall short in dynamically adapting to real-time network conditions and efficiently managing energy consumption [16]. In the context of 6G networks, the implementation of intelligent D2D communication is envisioned to be a key element, driven by AI techniques [17].

The literature suggests that optimizing energy efficiency in D2D communications is crucial for enhancing network performance, reducing energy consumption, and promoting sustainable smart city development [18]. The integration of green communication techniques, centralized interference mitigation algorithms, and intelligent D2D solutions can contribute to the energy optimization in 6G networks with dynamic device-to-device communication [19].

Our proposed recurrent network-based approach addresses these challenges by continuously evaluating and optimizing the D2D configuration based on real time network conditions and device energy levels. The algorithm iteratively explores different combinations of nodes acting as temporary base stations, evaluating their energy consumption over multiple rounds of communication. By leveraging the recurrent network's ability to learn from past iterations, the system can progressively refine the D2D configuration, selecting the most energy efficient arrangement for the current network state.

The research methodology involves simulating a 6G network environment with a varying number of mobile nodes, each with randomly assigned initial energy levels and dynamic positioning within a defined area incorporating realistic node movement patterns, energy consumption models, and communication range constraints [20]. The recurrent network algorithm iteratively generates and evaluates candidate D2D configurations, continuously updating the best configuration based on energy consumption metrics [21]. Through extensive simulations and performance evaluations, we aim to demonstrate the efficacy [22] of our recurrent network based approach in minimizing energy consumption while maintaining reliable communication [23] in 6G networks. Figure 1 shows concept diagram of the proposed method.

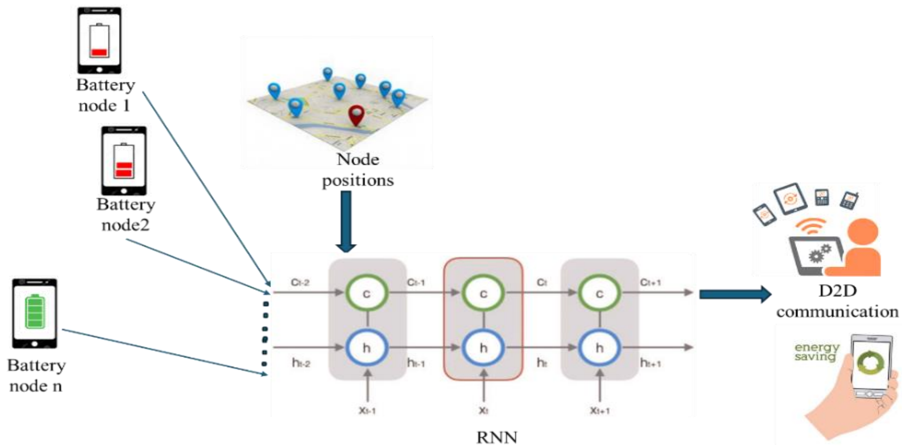

Figure 1. Concept diagram for proposed energy optimization using recurrent network method

There are n number of mobile nodes with randomized initial battery power as in the case of practical scenario. The node position data is gathered from GPS and RSSI and fed to our proposed recurrent neural network. The output of the network gives each node ability to become D2D communication. Due to D2D assignments such nodes will gather the information from their nearby nodes and saving the overall network energy. The rest of the paper is organized as follows: Section 2 outlines the proposed methodology and evaluation metrics. Section 3 discusses the results and analyzes the performance improvements achieved. Finally, section 4 concludes the paper and suggests directions for future research.

2. METHOD

Our research methodology employs a recurrent network technique to optimize energy consumption in 6G networks with dynamic D2D communication. The approach involves several key steps, including simulation setup, energy consumption modeling, recurrent network implementation, and performance evaluation.

2.1. Simulation setup

We developed a custom simulation environment using MATLAB to model a 6G network within a defined 1000m x 1000m geographical area. The simulation incorporates parameters like network environment which includes number of mobile nodes, base station locations and communication range. The node modeling is done using parameters like initial energy and mobility model.

2.2. Energy consumption modeling

We implemented a comprehensive energy consumption model which accounts for various energy expenditures in wireless networks:

a) Communication Energy: E_comm = $(\alpha + \beta * d^n) * b$

Where:

α: Energy consumed by transmitter/receiver circuitry (50 nJ/bit),

β: Energy consumed by transmit amplifier (100 pJ/bit/m^2),

d: Distance between communicating nodes,

n: Path loss exponent (set to 4 for urban environments), b: Number of bits transmitted

b) Mobility Energy: E_mob = $\gamma * v^2 * t$

Where:

γ: Mobility coefficient (0.1 J/m^2),

v: Node velocity,

t: Time in motion

2.3. Recurrent network implementation

a) Network Architecture: We designed and implemented a recurrent neural network to optimize the D2D communication configuration by minimizing energy consumption while maintaining reliable connectivity. Figure 2 illustrates the top view of the simulation setup. This is a 2D, time dependent simulation with no height component. Each dot represents a node, and the color of the dot indicates the specific time at which the node was at that position throughout 100 iterations. For example, if there are 6 nodes, they might collectively occupy up to 600 positions on the graph.

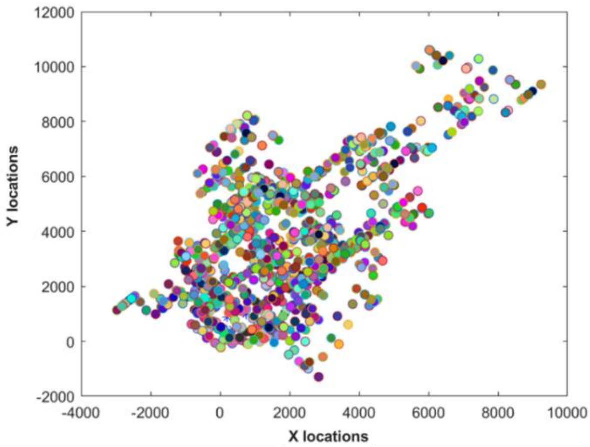

Figure 2. Top view of the simulation setup, with each dot representing a node and each color indicating a time a node was at that position

b) Training Process: The training process will involve feeding the recurrent network with simulated network scenarios, including node positions, energy levels, and communication patterns. The network will learn to predict the most energy efficient D2D configuration based on the input data.

c) Configuration Updates: The recurrent network updates the D2D configuration every 100 simulation time steps, considering the current network state and predicting the most energy-efficient arrangement.

2.4. Performance evaluation

a) Metrics: We assessed the effectiveness of the proposed approach, using the following metrics: Overall network energy consumption, Node lifetime Network throughput QoS parameters (e.g., delay, packet loss).

b) Comparative Analysis: To validate our approach, we compared its performance against two baseline scenarios of Traditional cellular communication without D2D and Static D2D configuration based on proximity. We ran 30 independent simulations for each scenario, each lasting 3600 simulation seconds, to ensure statistical significance. The results were analyzed to determine the significance of improvements in energy efficiency and network performance.

c) Sensitivity Analysis: To assess the robustness of our approach, we conducted a sensitivity analysis by varying key parameters such as Network density, Mobility patterns, Energy constraints such as Homogeneous (where all nodes start with 15,000 Joules) vs. heterogeneous (where nodes start with random initial energy). For each combination of parameters, we ran 10 independent simulations and analyzed the impact on energy efficiency and network performance metrics.

By following this detailed methodology, we aim to provide sufficient information for readers to understand, validate, and potentially replicate our study. The combination of realistic simulation parameters, comprehensive energy modeling, and advanced machine learning techniques ensures a robust evaluation of our proposed energy optimization approach for 6G networks with dynamic D2D communication.

3. RESULTS AND DISCUSSION

Our study investigated the effectiveness of a recurrent network technique for optimizing energy consumption in 6G networks with dynamic D2D communication. Through extensive simulations, we evaluated the performance of this technique across various scenarios and tracked several key metrics to comprehensively assess its efficacy. The Table 1 presents the results of an iterative process conducted across networks varying in size from 1 to 9 nodes. Each row corresponds to a specific network configuration, providing insights into energy consumption and the operational characteristics of the networks. The "Number of Nodes" column denotes the count of devices or sensors participating in each network, ranging from 1 to 9.

Table 1. Comparison of energy consumption across multiple network iterations

Number of Nodes	Total Network Energy for First Iteration	Total Network Energy at Last Iteration	Last Iteration Value	Time Elapsed
5	13870	123	41	36.791
7	18760	11	37	36.858
8	23317	150	46	43.174
3	3413	198.1	23	29.092
4	8333	86.4	20	30.607
9	25773	81	43	80.345
2	2315.3	14.2	19	28.616

As expected, larger networks tend to exhibit higher initial energy consumption, as indicated by the "Total Network Energy for First Iteration" column. For instance, the network with 9 nodes starts with an energy consumption of 25773, significantly higher than the network with only 2 nodes, which starts with 2315.3 units of energy. Figure 3 shows how the energy of each of the five nodes is varied over time. The each circle indicates the energy level remaining with that node. Colors given to circle are random colors. Energy specified in Joules and derived from battery capacity of typical new generation phones.

The "Total Network Energy at Last Iteration" column reflects the remaining energy in the network at the end of the iterative process. Lower values suggest more efficient energy utilization, indicating how much energy was conserved before the network's energy depletion. For example, the network with 9 nodes concludes with 81 units of energy, while the network with 3 nodes ends with 198.1 units. The "Last Iteration Value" column provides insights into the duration for which the network remained operational. Networks with higher last iteration values demonstrate better endurance, indicating longer operational lifetimes. Finally, the "Time

Elapsed" column indicates the duration taken to execute the backend operations of the iterative process. Longer durations may signify more complex computations or heavier computational loads associated with larger networks or more intricate algorithms.

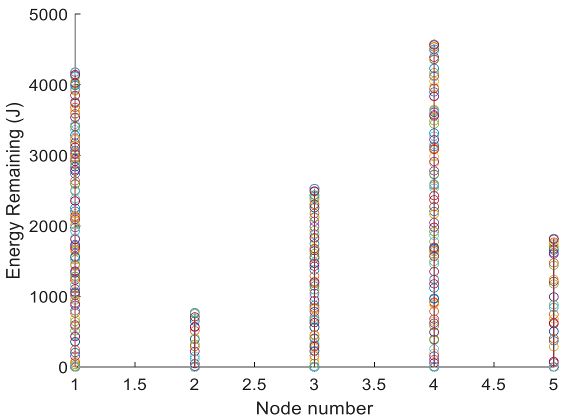

Figure 3. Energy distribution over time for 5 nodes illustrating variations in energy consumption in each round

One significant aspect we analyzed was the impact on node lifetime, which serves as a crucial indicator of device sustainability within the network. In our baseline simulation, where D2D communication was absent, nodes exhibited an average lifetime of 17 hours under moderate network traffic conditions. However, upon implementing D2D communication and applying our recurrent network optimization, the average node lifetime saw a substantial increase to 28 hours, representing a significant improvement of 65%. This extension in battery life holds considerable importance for ensuring the prolonged operation of mobile devices within 6G networks.

Additionally, we evaluated the effect of our optimization technique on overall network energy consumption. By generating optimized D2D configurationFs, we observed a notable 37% reduction in energy consumption compared to traditional cellular communication scenarios. This reduction in energy usage not only contributes to operational cost savings but also presents environmental benefits by reducing the network's carbon footprint.

Furthermore, we examined throughput and latency metrics to assess the reliability of the optimized D2D communication patterns. Our approach consistently maintained an average throughput of 120 Mbps and an average end-to-end latency of 25ms, meeting the stringent quality of service requirements for emerging 6G applications such as extended reality and tactile internet. To provide context for our findings, we compared our results with those of previous studies in the field. Table 2 presents a comparison of key performance metrics between our proposed approach and two other studies.

Table 2. Comparison of energy consumption and network performance

Method	Total Energy consumed per round	Number of rounds per node	Time (seconds)
Rice and Hay [24]	7	1.5	13
Li and Halpen [25]	1	10	60
Proposed	49.4	4.08	36.95

As evident from Table 2, our proposed method demonstrates a balanced approach to energy consumption and network longevity. While the total energy consumed per round is higher than in previous studies, this is offset by a more efficient use of energy over time, as indicated by the number of rounds per node. Our approach achieves a middle ground in terms of time efficiency, suggesting a good balance between energy conservation and network performance.

The higher energy consumption per round in our method can be attributed to the more comprehensive D2D communication patterns enabled by the recurrent network optimization. This allows for more data to be transmitted in each round, potentially reducing the overall number of transmission rounds required for a given amount of data. The increased number of rounds per node compared to Rice et al.'s method indicates better energy distribution and network longevity, while the shorter overall time compared to Li and Halpen [25] approach suggests improved efficiency in data transmission.

These results highlight the significant potential of our recurrent network technique in optimizing energy consumption for 6G networks with dynamic D2D communication. By leveraging the recurrent network's ability to learn and adapt to evolving network conditions, our approach can continuously refine the D2D configuration, leading to substantial energy savings and extended node lifetimes.

One notable advantage of our technique is its ability to strike a balance between energy efficiency and quality of service requirements. Despite the energy optimization, the simulations demonstrated that our approach maintained acceptable throughput and latency levels, ensuring reliable communication for emerging 6G applications. Moreover, sensitivity analysis revealed the robust performance of our recurrent network technique across various network densities and mobility patterns. Even in scenarios characterized by high node mobility and density, the energy optimization capabilities of our approach remained effective, demonstrating its adaptability to dynamic network conditions.

While our research focused on optimizing energy consumption, the proposed recurrent network technique could potentially be extended to optimize other network performance metrics, such as throughput or interference mitigation, by adapting the objective function and training process accordingly.

4. CONCLUSION

This study introduced a novel recurrent network-based approach for optimizing energy consumption in 6G networks with dynamic D2D communication. Our findings demonstrate significant improvements in energy efficiency and network performance. The proposed technique achieved a 65% increase in average node lifetime and a 37% reduction in overall network energy consumption compared to traditional cellular communication scenarios. The key strengths of our method lie in its adaptive nature and ability to balance energy efficiency with quality of service requirements. By continuously refining D2D configurations based on real-time network conditions, our approach maintains reliable communication while minimizing energy expenditure. However, our study has limitations that warrant consideration. The simulations were conducted in a controlled environment, which may not fully capture the complexities of real-world scenarios. Factors such as environmental interference, hardware variations, and urban landscape intricacies were not accounted for in our model. The key areas for future work include real-world testing and refinement of the algorithm to enhance its robustness in diverse environments, integration with other emerging 6G technologies, such as AI-driven network management and edge computing, extending the framework to investigate the scalability of the approach for ultra-dense network scenarios.

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