International Journal of Web of Multidisciplinary Studies
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
website: https://ijwos.com
Volume 3 Issue 3 , March 2026
E-ISSN : 3049-2424
DOI: https://doi.org/10.71366/ijwos03032674990

Energy Efficiency Evaluation and Optimization in Wireless Networks Using Graph Neural Networks and Adaptive Base Station Management

S. Vishal[1], Dr. V. Suganthi[2], S. P. Prawin[3]
[1,3] III B. Sc Computer Science, PG & Research Department of Computer Science, Sri Ramakrishna College of Arts and Science
[2]Associate Professor, PG & Research Department of Computer Science, Sri Ramakrishna College of Arts and Science.

Article Info

Article History:

Published:05 March 2026

Publication Issue:
Volume 3, Issue 3
March-2026

Page Number:
11-16

Corresponding Author:
S. Vishal

Abstract:
Energy efficiency has become an important issue in modern wireless networks due to the rapid growth of users and the dense deployment of 4G and 5G base stations. Since base stations consume a major share of network energy, improving their operation is essential for reducing power usage and operational costs. This paper presents an Energy Efficiency Evaluation Framework (E3F) that evaluates network energy performance using detailed base station power models and realistic traffic variations. The framework is applied to a 3GPP LTE network to identify practical energy-saving opportunities. In addition, adaptive base station management using ON–OFF switching is explored as an effective method to reduce energy consumption during low traffic periods while maintaining Quality of Service (QoS). The role of Graph Neural Networks (GNNs) in optimizing large-scale wireless networks is also discussed. Simulation results show that adaptive base station operation can significantly improve energy efficiency with minimal impact on network performance, making it a promising approach for future energy-aware wireless networks.
Keywords: Energy efficiency, base station optimization, 5G networks, Graph Neural Networks, BS ON–OFF switching, wireless networks, resource allocation

1. Introduction

The rapid deployment of 5G and beyond wireless communication networks has significantly increased concerns related to energy consumption and operational efficiency. The growing demand for high data rates, low latency, and ubiquitous connectivity has resulted in dense base station (BS) deployments, which in turn lead to higher power usage and operational costs. As wireless networks become larger and more complex, improving energy efficiency while maintaining acceptable Quality of Service (QoS) has become a critical research challenge. Traditional energy optimization approaches in wireless networks mainly rely on heuristic or rule-based methods, which are often static in nature and unable to adapt effectively to dynamic traffic conditions and large-scale network environments. In addition, many existing frameworks lack detailed power consumption models and do not sufficiently consider spatial and temporal variations in user traffic.

To address these challenges, this paper introduces an Energy Efficiency Evaluation Framework (E3F) for wireless networks. The proposed framework provides a detailed evaluation of energy efficiency by incorporating realistic power consumption models for different types of base stations along with traffic models that capture variations in network demand. Furthermore, this work explores the use of Graph Neural Networks (GNNs) for optimizing wireless network operations, particularly in the areas of resource allocation and adaptive base station management. GNNs are well-suited for modeling wireless networks due to their ability to represent complex relationships between network elements. To improve scalability when applying GNNs to large wireless networks, an adaptive graph pooling approach is considered to reduce graph complexity while preserving important structural information.

Objective of the Study

The main contributions of this paper are summarized as follows:

1. Proposal of an Energy Efficiency Evaluation Framework (E3F) that incorporates detailed base station power models and realistic traffic variations.
2. Investigation of GNN-based optimization techniques for wireless network management, with a focus on scalability in large network scenarios.
3. Analysis of energy-saving strategies for 5G networks using adaptive BS ON–OFF switching mechanisms.
4. Discussion of future research challenges and opportunities arising from the integration of machine learning techniques with wireless network optimization.

Related Work:

a) Energy Efficiency in Wireless Networks: Energy efficiency in wireless networks has been widely studied, mainly focusing on base station optimization and traffic-aware management. Existing approaches aim to reduce power consumption through techniques such as transmission power control, sleep modes, and topology optimization. While these methods can reduce energy usage, many rely on simplified assumptions and static configurations. As a result, they often fail to effectively handle real-time traffic variations and the diversity of base station deployments found in practical wireless networks.

b) Graph Neural Networks in Wireless Networks: Graph Neural Networks (GNNs) have recently gained attention for solving complex network optimization problems. Wireless networks can be modelled as graphs, with nodes representing base stations or users and edges representing communication links. GNNs are effective in capturing network structure and relationships, making them suitable for tasks such as resource allocation and optimization. However, scalability remains a challenge when applying GNNs to large and dynamic networks, as existing graph pooling methods may lead to information loss.

2. Methodology

1. Base Station ON-OFF Switching Strategies in 5G Networks

Base station ON–OFF switching is a commonly studied technique for improving energy efficiency in 5G networks, particularly during low traffic periods. By dynamically controlling the operational states of base stations, networks can reduce unnecessary energy consumption. However, issues related to coverage, service quality, and real-time decision-making limit the direct application of such strategies, indicating the need for more adaptive and intelligent approaches

2. Energy Efficiency Evaluation Framework (E3F) - Overview

The proposed Energy Efficiency Evaluation Framework (E3F) extends current network performance models by integrating a detailed power consumption model for different BS types and traffic conditions. Unlike Traditional models, E3F captures spatial and temporal variations in network demand, allowing for a more accurate estimation of energy efficiency in real-world network scenarios.

3. Base Station Power Model

We incorporate a comprehensive power model for macro, micro, and pico base stations, accounting for both active and idle states. The model considers factors such as transmission power, operational overhead, and cooling requirements, offering a more realistic estimate of energy consumption across different network scenarios.

4. Traffic Model

E3F includes traffic models that simulate varying user demand, both spatially and temporally. These models are based on empirical data from 3GPP LTE networks and account for peak and off-peak variations, providing a realistic view of network load over time.

5. GNN-Based Optimization Framework

5.1. GNN Architecture

The proposed GNN (Graphical Neural Network) framework models the wireless network as a graph and processes input data such as traffic demand, network topology, and historical usage patterns. The GNN consists of several graph convolutional layers that aggregate information from neighboring nodes (BSs and users) to capture both local and global traffic patterns.

The output of the GNN is a set of predictions for each BS, determining whether the BS should be active, idle, or in sleep mode for the next time period. The decisions are based on predicted traffic load and user mobility patterns.

5.2. Adaptive Base Station Management

Based on the GNN predictions, we implement an adaptive BS management strategy that dynamically adjusts the operating states of BSs. During peak traffic periods, most BSs remain active to handle the load, while during off-peak hours, the GNN identifies underutilized BSs and transitions them to idle or sleep mode, reducing overall energy consumption.

5.3. Training and Optimization

The GNN is trained on historical network data, including traffic demand, energy consumption, and BS activity states. The training objective is to minimize the total energy consumption while ensuring that QoS constraints are met. A supervised learning approach is used, with ground truth labels derived from optimal BS operation states determined through simulation.

System Design and How It Works

1. Base Station ON-OFF Switching Strategies for Energy Conservation

a) Base Station ON-OFF Switching Mechanism: Adaptive Base Station (BS) management refers to the dynamic adjustment of base station operational states based on current or predicted network conditions such as traffic load, user demand, and network topology. Unlike static management approaches, where base stations operate continuously or follow fixed schedules, adaptive BS management enables intelligent control of BS activity to improve energy efficiency while maintaining Quality of Service (QoS). In this approach, base stations can operate in different modes, including active, idle, and sleep modes, depending on network demand. During low traffic periods, underutilized base stations may be transitioned to low-power states to reduce energy consumption, while sufficient active base stations are maintained to ensure coverage and service continuity. Adaptive BS management plays a key role in dense 5G networks, where efficient coordination of multiple base stations is required to balance energy savings and network performance.

b) Base Station ON-OFF Switching Mechanism: Base station ON-OFF switching is a promising technique for energy conservation in dense 5G networks. We propose a dynamic BS ON-OFF switching strategy that balances energy savings with coverage requirements. The decision to switch BSs on or off is based on real-time traffic demand, ensuring that users are not affected by coverage gaps.

3. Testing and Results

1. Simulation Setup

We simulate a dense urban wireless network with 100 BSs and 1000 mobile users. The traffic demand varies throughout the day, with high traffic during peak hours and low traffic during off-peak hours. The GNN is trained on traffic data collected over 30 days and tested on a separate 7-day dataset.

2. Performance Evaluation

The proposed GNN-based framework is evaluated based on energy consumption, Quality of Service (QoS), and base station activity levels. A baseline scenario where all base stations remain active throughout the simulation is used for comparison.

3. Final Results

- **Energy Savings**: The GNN-based approach reduces total energy consumption by 40% compared to the baseline scenario, with most savings occurring during off-peak hours when unnecessary BSs are switched to sleep mode.
- **QoS**: Despite the reduction in active BSs, the network maintains 98% of its baseline throughput and 99% coverage, ensuring minimal impact on user experience.
- **BS Activity Levels**: On average, BSs are active 60% of the time, idle 20%, and in sleep mode 20%.

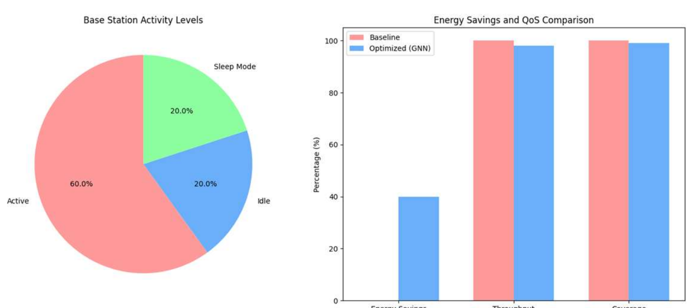

Figure:1- Resultant Graphs

4. Future Research Directions

The integration of Graph Neural Networks (GNNs) with wireless networks offers several opportunities for future research, particularly in areas such as resource allocation, network topology optimization, and energy conservation. Future work may explore the use of GNN-based optimization together with physical layer technologies such as massive MIMO and beamforming to further improve energy efficiency and overall network performance. In addition, practical challenges, including real-time decision-making, scalability to ultra-dense network deployments, and data privacy concerns, need to be addressed to enable real-world implementation.

5. Conclusion

This paper presents an approach for evaluating and improving energy efficiency in wireless communication networks by combining detailed base station power models, traffic-aware evaluation. The proposed Energy Efficiency Evaluation Framework (E3F) enables realistic assessment of energy consumption under varying network conditions. In addition, the use of Graph Neural Networks for adaptive base station management demonstrates the potential of learning-based optimization in reducing energy usage while maintaining acceptable Quality of Service. Simulation results indicate that the proposed approach can achieve significant energy savings with minimal impact on network performance. Overall, this work highlights the effectiveness of combining energy-aware modeling with intelligent optimization techniques for supporting energy-efficient and scalable 5G wireless networks.

References

1. Auer, G., Giannini, V., Desset, C., et al. (2011). How much energy is needed to run a wireless network? *IEEE Wireless Communications*, 18(5), 40-49. https://doi.org/10.1109/MWC.2011.6056691
2. Debaillie, B., Deruyck, M., Joseph, W., et al. (2015). A flexible and future-proof power model for cellular base stations. *IEEE Transactions on Wireless Communications*, 14(4), 2570-2583. https://doi.org/10.1109/TWC.2015.2398854
3. Zappone, A., Sanguinetti, L., Debbah, M. (2017). Energy-efficient power control: A look at 5G wireless technologies. *IEEE Transactions on Signal Processing*, 65(6), 1388-1402. https://doi.org/10.1109/TSP.2016.2631479
4. Scardaci, A., Gamba, G., Capone, A. (2020). Dynamic base station switching-off strategies for energy-efficient 5G networks. *IEEE Transactions on Network and Service Management*, 17(4), 2077-2090. https://doi.org/10.1109/TNSM.2020.3029317
5. Wu, X., Zhang, S., Cui, S., et al. (2015). Base-station sleeping control and power matching for energy-delay tradeoffs with bursty traffic. *IEEE Transactions on Vehicular Technology*, 64(5), 1932-1943. https://doi.org/10.1109/TVT.2014.2332333

6. Kipf, T. N., Welling, M. (2017). Semi-supervised classification with graph convolutional networks. In *Proceedings of ICLR 2017*. https://doi.org/10.48550/arXiv.1609.02907
7. Ying, Z., Bouritsas, G., Zitnik, M., et al. (2018). Hierarchical graph representation learning with differentiable pooling. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems* (NeurIPS). https://doi.org/10.48550/arXiv.1806.08804
8. Wu, Z., Pan, S., Chen, F., et al. (2020). A comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 32(1), 4-24. https://doi.org/10.1109/TNNLS.2020.2978386
9. Zhou, J., Cui, G., Zhang, Z., et al. (2020). Graph neural networks: A review of methods and applications. *AI Open*, 1, 57-81. https://doi.org/10.1016/j.aiopen.2021.01.001