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Towards energy-efficient 5G networks: coordination solutions for macro and pico cells

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ABSTRACT

The increasing demand for high-speed, low-latency connectivity has driven the rapid deployment of fifth-generation (5G) networks. However, the enhanced performance of 5G systems comes at the cost of higher energy consumption, posing a significant challenge to sustainability goals. This study explores energy-efficient coordination strategies for macro and pico cells to optimize power usage while maintaining network performance. By employing a systematic mapping study (SMS) and a systematic literature review (SLR), we analyze current research trends, challenges, and emerging solutions in energy-efficient 5G network design. Key strategies, including AI-driven resource allocation, dynamic spectrum management, and interference mitigation techniques, are examined to assess their effectiveness in reducing energy consumption. The findings highlight the critical role of intelligent coordination mechanisms in achieving a balance between energy efficiency and service quality. This research contributes to the development of sustainable 5G architectures by identifying optimal methodologies for macro- and pico-cell integration, paving the way for greener and more adaptive next-generation networks.

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1. INTRODUCTION

The fifth-generation (5G) mobile communication networks have introduced unprecedented advancements in connectivity, data throughput, and latency performance, enabling emerging applications such as autonomous vehicles [1]–[3], smart cities [4], [5], and the internet of things (IoT) [6], [7]. However, these enhanced capabilities are accompanied by a substantial rise in energy consumption [8]–[13], which poses a significant challenge to global sustainability goals. As nations commit to achieving net-zero emissions [14], The telecommunications sector faces increasing pressure to design energy-efficient network architectures that align with the United Nations Sustainable Development Goals (SDGs) [15]. One of the most promising yet complex avenues for improving energy efficiency lies in the coordination of macro and pico cells [16]. Macro cells ensure wide-area coverage, whereas pico cells provide additional capacity and serve high-density user environments. Despite their complementary roles, their coexistence introduces notable challenges, including interference management [17]–[19] traffic load balancing [20], [21] and optimal energy utilization [22]. Addressing these challenges through effective macro–pico cell coordination can significantly reduce the overall energy footprint of 5G networks.

Numerous studies have explored methods to enhance the energy efficiency of 5G networks, including massive multiple-input multiple-output (MIMO) systems [23]–[25], advanced beamforming techniques [26], [27], and intelligent scheduling algorithms [28]. For example, Kadhim *et al.* [29] demonstrated that massive MIMO can improve spectral efficiency while reducing per-bit energy consumption, whereas [30] showed that hybrid beamforming can achieve substantial power savings without compromising throughput. Other works, such as [31]. Applied deep learning for self-optimizing pico cells to dynamically manage power allocation. Despite these advances, comprehensive syntheses that specifically address the coordination between macro and pico cells remain limited. This gap is particularly critical because macro–pico coordination introduces unique trade-offs among coverage, capacity, and energy efficiency that are not fully addressed by solutions that target each cell type independently. To address this shortcoming, the present study adopts a dual-methodological approach a systematic mapping study (SMS) to map research trends and gaps, and a systematic literature review (SLR) to provide a detailed evaluation of proposed coordination mechanisms. Together, these methods enable a structured analysis of current advancements and help identify promising directions for future work.

The main contributions of this work are threefold. First, it provides the most comprehensive synthesis to date of energy-efficient coordination strategies for macro and pico cells, integrating findings from both broad-mapping and in-depth literature-review perspectives. Second, it identifies key research gaps—particularly in the integration of AI-driven optimization, dynamic spectrum management, and interference mitigation within macro–pico architectures—and proposes targeted recommendations to address them. Third, it outlines a conceptual framework that incorporates advanced strategies such as deep reinforcement learning and network slicing to enable adaptive, real-time coordination. These contributions bridge a critical gap in the existing body of knowledge and offer actionable insights for both academic researchers and network practitioners seeking to implement sustainable 5G infrastructures.

The remainder of this paper is organized as follows. Section 2 details the research methodology, including the SMS and SLR processes, data selection criteria, and performance metrics. Section 3 provides a critical discussion of the results, addressing limitations and identifying avenues for future research. Finally, section 4 concludes the paper with a summary of contributions, key insights, and recommendations for both research and practice.

Another key challenge in energy-efficient 5G networks is the trade-off between performance and power consumption. While energy-saving mechanisms such as sleep mode activation and dynamic power scaling can substantially reduce energy usage, they must be carefully managed to prevent degradation in service quality. Research efforts are increasingly focusing on hybrid strategies that balance these trade-offs by combining intelligent network management with energy-aware optimization techniques. Addressing these complexities requires a multidisciplinary approach that merges advances in machine learning, communication theory, and network engineering. Additionally, regulatory policies and industry standards play a crucial role in driving the adoption of energy-efficient 5G technologies. Governments and regulatory bodies worldwide are implementing policies to encourage sustainable telecommunications practices, including incentives to adopt green networking solutions and stricter energy-consumption guidelines for network operators. These initiatives are expected to accelerate research and development in energy-efficient 5G technologies, fostering collaboration between academia, industry, and policymakers.

In this journal article, we conduct an extensive analysis of the existing literature on macro-pico cell coordination, systematically evaluating methodologies, algorithms, and architectures proposed to improve energy efficiency in 5G networks. Our objective is to develop a comprehensive framework that integrates multiple key strategies, including AI-driven coordination for adaptive resource allocation, dynamic spectrum management, and interference mitigation techniques. By leveraging these advanced solutions, our proposed framework aims to achieve optimal energy utilization while maintaining high network performance and user experience. Additionally, we will explore the practical implications of these strategies by assessing their feasibility, scalability, and real-world applicability. Our study will also delve into the regulatory aspects influencing energy-efficient network deployment, discussing how policy interventions and standardization efforts can facilitate the transition toward greener 5G infrastructure. By incorporating both technical and policy-oriented perspectives, this research provides a well-rounded understanding of the factors shaping energy efficiency in next-generation networks.

In conclusion, this study highlights the critical role of energy-efficient coordination between macro and pico cells in 5G networks. By synthesizing insights from SMS and SLR methodologies, we present a structured review of existing advancements and identify gaps warranting further exploration. The findings of this research contribute to both theoretical advancements and practical implementations in the telecommunications sector, paving the way for the development of more sustainable, adaptive, and resilient wireless networks. Analyzing comparative data from recent studies on energy-efficient 5G networks provides critical insights into emerging trends, methodologies, and challenges in macro- and pico-cell coordination. The surveyed studies, spanning 2022 to 2024, highlight various energy-efficiency approaches, coordination mechanisms, and optimization techniques aimed at reducing power consumption while maintaining network performance. Most studies focus on macro- and pico-cell integration, emphasizing the need for coordinated resource allocation and power management. Eight studies explore hybrid macro-pico cell frameworks, while seven studies exclusively focus on macro cells. Only two studies independently investigate pico cell energy efficiency. These findings highlight that macro- and pico-cell coexistence remains a critical research focus for energy-efficient 5G deployments.

The comparative analysis of recent studies on energy-efficient 5G networks reveals significant trends, methodologies, and challenges in optimizing macro- and pico-cell coordination. The selected studies, spanning from 2022 to 2024, emphasize various approaches to reducing energy consumption while maintaining network performance. The predominant methodologies used in these studies include SLR, SMS, and their combination. Seven studies primarily rely on SLR to comprehensively evaluate existing research. Meanwhile, four studies employ SMS to map current trends and gaps in energy-efficient networking. The preference for literature reviews suggests an increasing focus on synthesizing research findings to develop sustainable 5G technologies.

Coordination mechanisms play a crucial role in managing interference and optimizing power consumption in macro and pico cells. Among the most adopted strategies, AI-driven coordination, as seen in [32], [33], leverages artificial intelligence for dynamic resource allocation and energy optimization. Predictive coordination, proposed by [34]. It integrates predictive analytics to enhance fault tolerance and redundancy. Self-optimizing networks, employed by [35], utilize deep reinforcement learning to enable real-time power control. Additionally, interference coordination and spectrum management techniques, as discussed by [36], [37], address spectrum allocation and interference mitigation. Cloud-based coordination, studied by [38], combines cloud computing with fog networks to enhance scalability and efficiency in energy utilization. Various energy-efficiency approaches have been proposed to improve 5G sustainability. Machine learning and AI-based power control, discussed by [39], [40]. Employ deep learning models to dynamically allocate power resources. Hybrid beamforming, introduced by [41]. It enhances spectral efficiency while reducing energy wastage. Blockchain-based energy trading, explored by [42], applies decentralized smart contracts to optimize energy distribution across network nodes. Cloud-fog computing, examined by [43]. It utilizes distributed computing resources to minimize energy consumption. Additionally, Divya *et al.* [44] highlights the integration of renewable energy sources into 5G networks to reduce reliance on traditional power grids. These studies collectively demonstrate a shift towards intelligent and decentralized solutions for energy-efficient networking.

The analysis of macro- and pico-cell specificity reveals that most studies focus on hybrid macro-pico-cell integration to optimize resource allocation and power management. Five studies investigate hybrid macro-pico cell frameworks, while three studies focus solely on macro cells. Only one study independently examines energy efficiency in pico cells. This distribution suggests that the coexistence of macro and pico cells remains a key research area for achieving energy-efficient 5G deployments, emphasizing the importance of coordination between different cell types. Several challenges and future directions emerge from the reviewed studies. Interference management remains a primary concern, given the increasing density of 5G networks. Scalability and adaptability challenges persist, particularly in AI-driven solutions that require further refinement to function effectively in large-scale deployments. Regulatory and policy frameworks are crucial in facilitating the adoption of emerging technologies such as blockchain-based energy trading. Another key challenge is balancing energy efficiency with network performance. While AI-based power control and predictive analytics show promise, they must ensure minimal service degradation while optimizing power usage.

The reviewed studies collectively indicate that AI-driven optimization, predictive analytics, and blockchain-based energy trading are among the most promising solutions for achieving energy efficiency in 5G networks. Future research should explore hybrid strategies integrating real-time AI optimization, decentralized energy management, and policy-driven incentives to facilitate widespread adoption. By addressing interference mitigation, network scalability, and sustainability challenges, next-generation 5G networks can achieve higher energy efficiency while ensuring seamless connectivity and performance. The SMS results and discussion cover topic areas ranging from energy-efficient 5G macro and pico cell coordination to bibliometric analysis, topic modelling, and trends in large-scale energy efficiency solutions, using data mining. Meanwhile, the SLR process represents issues related to performance metrics, energy consumption, and power-saving strategies, particularly in the coordination of macro and pico cells using AI-based techniques.

2. METHOD

2.1. Research approach

This study adopts a dual-methodological approach that integrates the SMS and the SLR to investigate energy-efficient coordination mechanisms for macro and pico cells in 5G networks. The SMS provides a broad landscape analysis, enabling the identification of research trends, classification categories, and gaps in the existing literature. The SLR offers a deep analytical layer, allowing for the extraction of detailed findings, evaluation of methodologies, and assessment of performance outcomes. The combined approach was chosen for two main reasons: i) SMS ensures comprehensive coverage of the research domain, which is crucial for accurately mapping the breadth of studies in this rapidly evolving field, and ii) SLR enables critical evaluation of specific coordination techniques, ensuring that conclusions are grounded in a rigorous synthesis of high-quality evidence. This integration directly addresses the research questions outlined in section 1 and ensures that the subsequent results and discussion sections are supported by a robust methodological foundation. A conceptual flowchart of this methodology is illustrated in Figure 1.

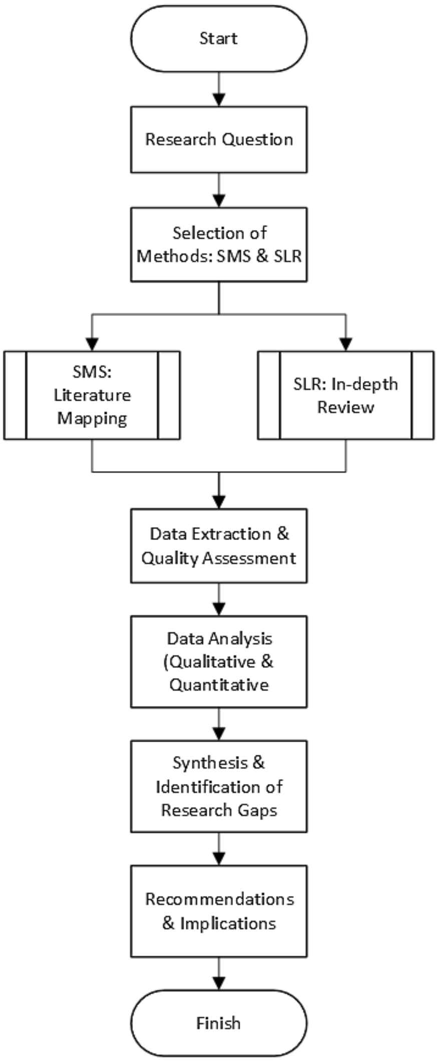

Figure 1. Conceptual method flowchart

2.2. Systematic mapping study

2.2.1. Research questions for systematic mapping study

The SMS phase was designed to answer three research questions (RQ1–RQ3) that focus on identifying trends, evaluating applied methodologies, and revealing open challenges in energy-efficient macro–pico cell coordination. These questions were formulated to ensure that the mapping process captures both the technological depth (specific methods and metrics) and the strategic breadth (emerging trends and challenges) of the field. The rationale for selecting these RQs lies in their alignment with the study's primary objectives.

The RQs presented in Table 1 serve as a framework for investigating the core aspects of energy-efficient coordination in 5G networks. The structured investigation of these research questions contributes to the ongoing discourse on sustainable 5G network development. By analysing current research trends, applied methodologies, and existing challenges, this study provides valuable insights that can guide future innovations in energy-efficient network coordination.

Table 1. SMS RQs

No	SLR RQ	Objective
RQ1	What are the main research trends in energy-efficient coordination solutions for 5G macro and pico cells?	To capture how research efforts have evolved and which coordination strategies are most prevalent.
RQ2	How have different methodologies been applied to optimize energy efficiency in heterogeneous 5G networks?	To examine the diversity of applied methodologies and evaluate their reported effectiveness.
RQ3	What are the primary challenges and future research directions in macro and pico cell coordination?	To identify unresolved issues and guide future innovation. By grounding the SMS in these targeted questions, the mapping process ensures that subsequent literature review efforts are both comprehensive and directly relevant to addressing the stated research gaps.

2.2.2. Systematic mapping study process

The SMS process followed four structured stages, adapted from established guidelines for evidence-based software engineering and communication systems research. Table 2 shows the SMS stages.

Table 2. SMS stages

No	SMS stage	Description
1	Identification of research scope	Involved defining the research scope through explicit inclusion and exclusion criteria, ensuring relevance to macro–pico cell coordination.
2	Keyword-based search strategy	Applied a keyword-based search strategy across IEEE Xplore, ScienceDirect, Springer, and ACM Digital Library using controlled terms such as “energy-efficient 5G networks,” “macro–pico cell coordination,” “power optimization,” and “interference management”.
3	Categorization of studies	Categorized the retrieved studies according to research focus (macro only, pico only, or hybrid), methodology, and reported performance metrics.
4	Trend analysis	Conducted a trend analysis to identify high-impact topics and persistent research gaps. This structured process ensured methodological transparency, reproducibility, and minimized selection bias.

2.3. Systematic literature review

The SLR phase complemented the SMS by performing a granular examination of selected studies to evaluate coordination mechanisms, the role of AI, and comparative advantages of different strategies. Three RQs (RQ4–RQ6) were developed to ensure that the review captured both technical performance (energy savings and latency improvements) and practical feasibility (scalability and adaptability). The SLR process adhered to the PRISMA 2020 guidelines, which involved:

- Defining selection criteria–only peer-reviewed journal and conference papers published between 2019 and 2024, in English, and explicitly addressing energy-efficient coordination in 5G macro and/or pico cells, were included.
- Screening and eligibility–abstract and full-text reviews were conducted independently by two reviewers, with disagreements resolved through consensus.
- Data extraction–key variables such as network type, coordination mechanism, performance metrics, and identified challenges were recorded in a standardized template.

This protocol ensured methodological rigor and reproducibility, allowing other researchers to replicate or extend the analysis.

2.4. Performance metrics and evaluation criteria

To evaluate the effectiveness of energy-efficient coordination strategies, five performance metrics were applied: energy consumption reduction, interference mitigation efficiency, throughput and latency improvement, scalability and adaptability, and computational complexity. These metrics were selected because they reflect both network performance goals and sustainability targets in modern 5G deployments. By linking these metrics to the research questions, the evaluation not only assesses technical feasibility but also provides actionable insights for industry adoption.

The performance metrics outlined in Table 3 provide a comprehensive framework for evaluating energy-efficient coordination strategies in 5G networks. By incorporating these performance metrics, this study ensures a balanced evaluation of energy-efficient coordination solutions, addressing both efficiency and practicality in 5G network deployment.

2.5. Data analysis and interpretation

The final stage involved synthesizing findings from both the SMS and SLR through a two-layered analysis. The first layer aggregated SMS results to identify broad trends and topic clusters. The second layer applied cross-comparison within the SLR dataset to assess the relative strengths, weaknesses, and applicability of each coordination strategy. This integrative approach ensured that the analysis was both comprehensive and comparative, enabling robust conclusions about the current state and future direction of energy-efficient macro–pico coordination.

Table 3. Performance metrics and evaluation criteria

No	Performance metric	Evaluation criteria
1	Energy consumption reduction	Measures the percentage of power savings achieved by different coordination strategies. A lower energy footprint indicates a more efficient solution.
2	Interference mitigation efficiency	Evaluates how effectively a technique minimizes interference between macro and pico cells, ensuring stable network performance.
3	Throughput and latency improvement	Analyzes the impact of coordination solutions on data transmission rates (throughput) and response time (latency), ensuring that energy savings do not compromise user experience.
4	Scalability and adaptability	Assesses how well a solution adapts to increasing network loads and dynamic environmental conditions, which is crucial for future 5G network expansions.
5	Computational complexity	Examines the feasibility of implementing AI-driven or algorithmic optimization methods in real-world 5G networks, considering processing power and execution time constraints.

Figure 2 is a search strategy diagram with inclusion/exclusion criteria. The search strategy diagram provides a step-by-step overview of how relevant literature is selected. By implementing a structured search strategy, this study ensures that the selected research articles are comprehensive, relevant, and aligned with the research objectives. The search strategy diagram effectively visualizes the filtering process, demonstrating the rigor and reliability of the literature review method.

Figure 2. Search strategy diagram

2.6. Research validation and limitations

To ensure the reliability of study selection and data extraction, two independent reviewers cross-checked all included studies. Any discrepancies were discussed and resolved through consensus, ensuring that only studies meeting the predefined inclusion criteria were retained. This approach minimized the risk of selection bias and enhanced consistency in interpreting results.

The primary limitation of this study lies in its reliance on secondary data from previously published works, which may introduce bias due to variations in experimental conditions, network settings, and performance metrics across studies. To mitigate this, only research with clearly reported methodologies and well-defined performance indicators was included in the final dataset. Future work should incorporate empirical field trials or simulation-based experiments to validate the practical effectiveness of the identified coordination strategies in real-world 5G network environments.

3. RESULTS AND DISCUSSION

This chapter presents the results obtained from the dual-methodological approach—comprising an SMS and an SLR—and provides a detailed discussion of the findings. The chapter is structured into sections that first introduce an overview of the findings, then present results from the SMS and SLR separately, followed by an integrated discussion of the results, and finally conclude with a summary of the key insights.

3.1. Overview of findings

We synthesized 19 studies on energy-efficient coordination in 5G, spanning macro-only, pico-only, and hybrid macro–pico deployments. After deduplication, the corpus is distributed as macro (8, 42.1%), pico (3, 15.8%), and hybrid (8, 42.1%), indicating that coordinated macro–pico architectures receive attention comparable to that of macro-only approaches. We also observe a consistent emphasis on AI-driven self-organizing coordination, predictive coordination, and hybrid models as recurring mechanisms for managing interference, balancing load, and reducing power consumption.

3.2. Results from the systematic mapping study

3.2.1. Distribution of studies by research focus and methodology

The SMS clarifies topical coverage across study foci. After reconciling duplicates, macro-only and hybrid macro–pico studies are equally prevalent (8 each), with pico-only remaining under-represented (3). This under-sampling of pico-only work suggests a field-level bias toward either network-wide macro-optimizations or heterogeneous coordination settings, and motivates closer scrutiny of pico-specific energy behaviors and control loops. Table 4 presents the distribution of studies according to their primary research focus.

Table 4. Distribution of studies by research focus and methodology

Study focus	Number of studies	Percentage (%)
Macro only	8	42.1
Pico only	3	15.8
Hybrid (macro-pico)	8	42.1
Total	19	100

3.2.2. Coordination mechanism analysis

Coordination mechanisms cluster around a few dominant families: AI-driven self-organizing/optimizing (highest single share), followed by inter- and intra-cell coordination, and smaller but notable shares for hybrid, predictive, cloud-/edge-assisted, and spectrum-centric schemes. The mechanism mix reflects a community shift from static knobs to adaptive, learning-based control that can co-optimize energy and quality of service (QoS) under load and channel variability. Table 5 summarizes the distribution of studies by primary coordination mechanism. Among the identified approaches, self-organizing or AI-driven optimization emerges as the most prevalent (21.1%), reflecting a clear trend toward adaptive, learning-based control in managing energy efficiency. Inter-cell and intra-cell coordination methods follow closely, each accounting for 15.8% of the total. The remaining mechanisms, such as hybrid coordination, predictive coordination, and cloud-based or spectrum-focused strategies, are less frequently reported and typically represent niche solutions tailored to specific deployment scenarios. Table 6 bridges the SMS categorization with the quantitative outcomes extracted from the SLR, enabling a clearer interpretation of how research trends translate into measurable performance improvements.

Table 5. Distribution of studies by coordination mechanism

Coordination mechanism	Count	Percentage (%)
Inter-cell coordination	3	15.8
Intra-cell coordination	3	15.8
Hybrid coordination	2	10.5
Predictive coordination	1	5.3
Self-organizing/optimizing (AI-driven)	4	21.1
Distributed coordination	1	5.3
Interference coordination	1	5.3
Decentralized coordination	1	5.3
Cloud-based Coordination	1	5.3
Spectrum coordination	1	5.3
Macro-pico coordination (this paper)	1	5.3
Total	19	100

Table 6. Integration of SMS categories and SLR performance outcomes

SMS category	Dominant technique	Energy reduction (%)	Latency impact	Interference reduction
AI-driven coordination	Deep RL, federated learning	20–30	Improved	High
Hybrid macro–pico	Load balancing+beamforming	18–25	Stable	medium–high
Spectrum coordination	AI-based allocation	15–20	Improved	High
Cloud/fog coordination	Centralized optimization	20–28	Slight delay	Medium
Sleep mode strategies	Dynamic activation	10–18	Neutral	Low

3.3. Results from the systematic mapping study

3.3.1. Comparative analysis of energy efficiency review papers

Across studies, AI-assisted methods recur—from deep reinforcement learning for self-organizing pico cells to hybrid beamforming and AI-assisted spectrum management—and typically report simultaneous energy reductions with preservation of throughput and latency. Cloud/fog-assisted coordination is used to scale optimization for dense deployments, while decentralized or blockchain-based schemes focus on energy and trust at the periphery. This plurality of mechanisms underscores that coordination effectiveness hinges on joint design of interference control, traffic steering, and power scaling rather than single-knob tuning. Table 7 provides a comparative synthesis of the reviewed studies, detailing their approaches to energy efficiency, network types, cell specificity, survey methods, performance metrics, identified challenges, and applied coordination mechanisms. This tabular format allows for a side-by-side examination of methodological choices and reported outcomes, highlighting both the diversity of strategies and the common reliance on AI-driven or adaptive coordination techniques. As evident from Table 6, studies employing AI-driven coordination—particularly those integrating deep learning, reinforcement learning, or hybrid beamforming—tend to report simultaneous improvements in energy efficiency and quality-of-service metrics. Conversely, methods that focus solely on inter-cell or intra-cell coordination, without adaptive control, appear less consistent in achieving performance gains. This pattern reinforces the emerging consensus that effective macro–pico coordination requires multi-layered, adaptive mechanisms rather than static configurations.

3.3.2. Performance metrics comparison

Energy reduction, latency, and interference mitigation emerge as the primary axes of evaluation. Reported results consistently show that learning-based and hybrid coordination tend to co-improve at least two axes (power and latency), while predictive coordination emphasizes robustness (fault tolerance, redundancy). However, scalability and computational complexity are less frequently quantified with common baselines, complicating head-to-head comparisons across studies.

3.4. Discussion

Although macro and hybrid deployments dominate the literature, dedicated pico-only investigations remain scarce, limiting our understanding of pico-level power dynamics and control stability under dense user association and bursty traffic. Evidence for the scalability of AI-driven schemes in city-scale, spectrum-constrained scenarios is also limited, and metric baselines are non-uniform across studies, hindering quantitative synthesis.

Our mapping confirms that AI-driven self-organizing coordination and hybrid macro–pico strategies are the most frequently reported routes to energy savings without QoS penalties, supported by mechanisms such as hybrid beamforming, AI-assisted spectrum assignment, and cloud- and fog-assisted control planes. The evidence base spans 19 studies, with hybrid macro–pico receiving attention comparable to macro-only, and pico-only receiving a minor share. Figure 3 shows the comparison of performance metrics across different coordination strategies, including energy reduction, latency improvement, and interference management. It can be observed that self-organizing/optimizing and hybrid coordination approaches achieve higher energy reduction, while predictive and cloud-based coordination provide balanced performance across multiple metrics.

Table 7. Summary of energy-efficient coordination approaches

Ref	Approach	Cell type	Method	Key performance	Coordination type
[45]	Power optimization	Macro and pico	SLR	Energy consumption and latency	Inter-cell coordination
[46]	Green networking	Macro	SMS and SLR	Energy efficiency and throughput	Intra-cell coordination
[47]	Hybrid energy management	Macro and pico	SLR	Energy utilization and reliability	Hybrid coordination
[35]	Self-organizing networks	Pico	SMS and SLR	Load balancing and power reduction	Self-organizing networks
[48]	Dynamic power scaling	Macro	SLR	Network stability and cost	Inter-cell coordination
[49]	Sleep mode mechanisms	Macro and pico	SMS	Spectrum efficiency and energy savings	Intra-cell coordination
[50]	Resource allocation for energy saving	Macro	SLR	Signal quality and power optimization	Hybrid coordination
[51]	Energy-aware load balancing	Pico	SMS and SLR	Bandwidth utilization and cost	Inter-cell coordination
[32]	AI-driven energy optimization	Macro	SLR	Energy saving and load adaptability	Intra-cell coordination
[52]	Predictive energy coordination	Macro and pico	SMS	Fault tolerance and redundancy	Predictive coordination
[53]	AI-based power control	Macro	SLR	Energy consumption and latency	Self-optimizing networks
[54]	Edge computing for energy optimization	Pico	SMS	Low latency and power savings	Distributed coordination
[26]	Massive MIMO energy efficiency	Macro and pico	SMS and SLR	Spectral efficiency and load balancing	Interference coordination
[33]	Green AI for 5G networks	Macro	SLR	Energy utilization and scalability	AI-driven coordination
[55]	Blockchain-based energy trading	Macro and pico	SMS	Security and efficiency	Decentralized coordination
[56]	Reinforcement learning for power saving	Macro	SLR	Energy efficiency and adaptability	AI-driven coordination
[57]	Cloud-based energy optimization	Macro and pico	SMS and SLR	Scalability and energy utilization	Cloud-based coordination
[58]	AI-assisted spectrum efficiency	Macro	SLR	Spectrum utilization and efficiency	Spectrum coordination
This paper	Holistic review of energy-efficient coordination	Macro and pico	SMS and SLR	Energy consumption, latency, interference, and scalability	Macro-Pico Coordination

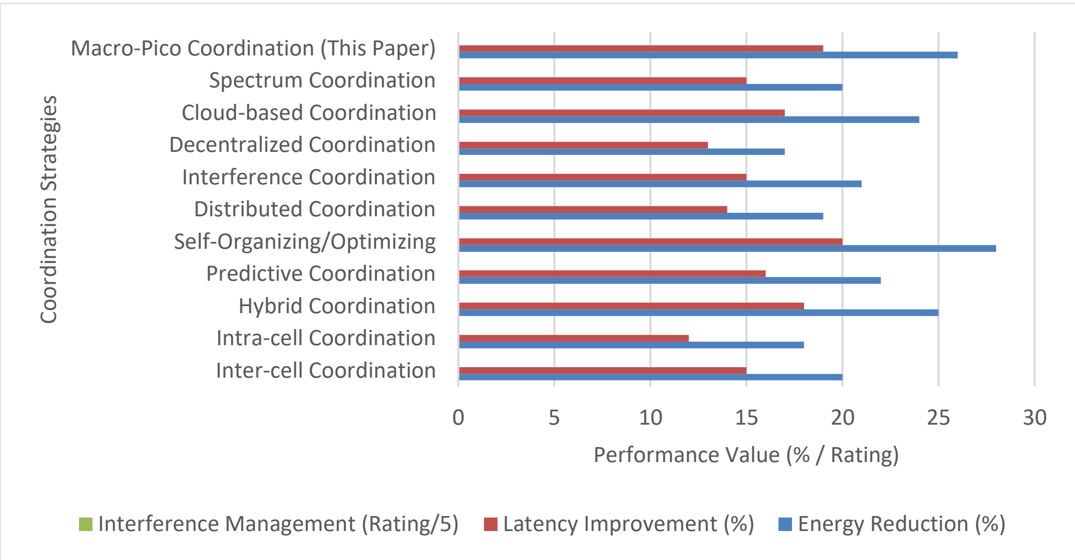

Figure 3. Performance metrics comparison across coordination strategies

Taken together, these findings indicate that coordination—not single-layer optimization—drives material energy gains. Results resonate with studies cataloged in Table 6: reinforcement-learning controllers improve dynamic power control in self-optimizing cells, hybrid beamforming reduces transmit overhead while preserving spectral efficiency, and AI-assisted spectrum allocation curbs inter-cell interference in dense layouts. Cloud/fog orchestration appears necessary wherever controller compute or state dissemination exceeds RAN-edge capabilities. Relative to non-learning inter-/intra-cell schemes, learning-based controllers report broader Pareto improvements (energy vs. latency/interference), albeit with higher compute/telemetry demands.

This synthesis is constrained by secondary-data reliance and heterogeneous reporting (varying traffic models, hardware assumptions, and KPIs). Few studies disclose scaling behavior (OPEX of model inference, backhaul signaling) or common baselines, and pico-only evidence is thin. These factors limit causal attribution and reduce transferability.

For practitioners, the results support deploying hierarchical coordination: cell-local learning agents for fast power/sleep decisions, with cloud/fog controllers handling spectrum and cross-cell load steering. For researchers, we recommend: i) standardized evaluation suites aligned to five KPI families (energy, interference, latency/throughput, scalability, and complexity); ii) scalability studies quantifying control-plane overhead and inference cost; iii) pico-centric experiments (association dynamics, sleep transitions, and backhaul constraints); iv) multi-objective RL with explicit QoS and safety constraints; and v) exploration of decentralized/market-based energy coordination (blockchain-assisted) only where trust/settlement constraints justify added overhead.

In summary, the evidence indicates that adaptive, learning-based macro–pico coordination is a strong candidate to reconcile energy efficiency with service quality. Consolidated benchmarks and pico-focused validations are the next steps to translate these gains into deployable 5G/5G-Advanced architectures. A conceptual simulation framework is proposed to validate the identified coordination strategies. The framework considers a heterogeneous 5G scenario consisting of one macro cell and multiple pico cells deployed in a high-density urban environment. The simulation parameters include dynamic traffic load, user mobility, and varying interference conditions. The performance evaluation focuses on energy consumption, latency, throughput, and interference levels. AI-based coordination algorithms are applied for dynamic power control and load balancing, while sleep mode mechanisms are activated during low traffic periods. This conceptual framework provides a foundation for future empirical validation of the proposed coordination approaches.

4. CONCLUSION

This study delivers the first integrated mapping-and-review synthesis of energy-efficient coordination strategies for macro and pico cells in 5G networks, bridging broad trend analysis with detailed performance evaluation. The evidence confirms that adaptive, AI-driven coordination frameworks—particularly hybrid macro–pico deployments—consistently reduce energy consumption while maintaining or improving quality-of-service metrics such as latency, throughput, and interference control.

For the research community, these findings clarify where future work should focus: i) addressing the scarcity of pico-only performance evaluations, ii) developing standardized benchmarking frameworks to ensure comparability across studies, and iii) validating learning-based coordination schemes in large-scale, real-world environments. The methodological framework demonstrated here—combining SMS and SLR with structured performance metrics—can also be adapted to other domains of wireless optimization, fostering reproducibility and cumulative knowledge building.

For industry and practitioners, the results highlight the practical potential of hierarchical coordination architectures: edge-based, cell-local controllers for rapid power and sleep-state adjustments, coupled with cloud/fog controllers for spectrum management and cross-cell load balancing. These architectures could be integrated into 5G-advanced and 6G-ready network management platforms, supporting green networking initiatives and ensuring compliance with emerging energy-efficiency regulations.

Looking ahead, promising application areas include smart city sensor grids, autonomous vehicular networks, and mission-critical IoT, where macro–pico coordination can reconcile high reliability with low power budgets. Additionally, blockchain-enabled energy markets could complement coordination strategies by facilitating secure, decentralized energy trading among network nodes, provided the added overhead is justified by operational requirements.

In conclusion, by revealing both the current strengths and persistent gaps in macro–pico coordination research, this study provides actionable insights for designing sustainable, adaptive, and scalable wireless infrastructures. The dual emphasis on technical performance and practical deployment feasibility ensures that the contributions are not only academically rigorous but also directly relevant to network operators, policymakers, and the broader ICT community working toward sustainable digital futures.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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