Vol.4, No.1, Page 1496- 1506, 2026 https://doi.org/10.59628/jast.v4i1.2291 ISSN 2958-9568 JAST

SUN PUBLISHER

مجلة جامعة صنعاء للعلوم التطبيقية والتكنولوجيا
Sana'a University Journal of Applied Sciences and Technology
https://journals.su.edu.ye/index.php/jast/

AI-Driven Self-Organizing Networks (SON) for 5G OPEX Reduction: A Comprehensive Survey and Conceptual Framework

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ABSTRACT

This paper investigates the application of Artificial Intelligence (AI) in Self-Organizing Networks (SON) for 5G networks, focusing on coverage enhancement and reduction of Operational Expenditures (OPEX). A conceptual AI-Self-Organizing Networks (SON) framework integrated with O-RAN architecture is proposed, and an illustrative Python-based simulation is conducted to demonstrate potential trends in coverage probability, energy consumption, and estimated OPEX savings. The simulation results indicate that AI-SON can achieve near-optimal coverage (coverage probability 0.9985) while reducing energy usage and maintenance costs, with an estimated OPEX reduction of 2030% compared to baseline strategies. The study clarifies that the simulation is illustrative and not experimentally validated, providing a foundation for future rigorous evaluations.

ARTICLE INFO

Keywords:
Self-Organizing Network, AI-SON, 5G, O-RAN, Operational Expenditures (OPEX), Reinforcement Learning

Article History:
Received: 27-September-2025,
Revised: 10-November-2025,
Accepted: 13-November-2025,
Available online: 29 January 2026.

1. INTRODUCTION

The fifth generation (5G) of mobile networks represents a substantial evolution from previous generations, designed to support a diverse set of applications and business models, including enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), massive machine-type communications (mMTC), smart cities, automotive systems, and high-tech manufacturing [1–6].

Unlike 4G systems, which primarily offered a one-size-fits-all mobile broadband solution, 5G networks must simultaneously satisfy heterogeneous requirements in network functionalitiessuch as security, mobility management, and policy controland stringent performance metrics including peak data rates above 10 Gbps, end-to-end latency below 1 ms, high reliability (up to 10^{-5}), and mobility support up to 500 km/h [2, 7–14] .

To address these requirements, network slicing has become a foundational mechanism that enables operators to create multiple logical networks with dedicated functionalities, while sharing the same physical infrastructure. Each network slice can be optimized for specific service types (e.g., eMBB, URLLC, and mMTC) or specific tenants, guaranteeing an appropriate quality of service and resource isolation. For example, a network slice for smart metering may prioritize small, infrequent transmissions with minimal mobility support, whereas a public safety slice may guarantee minimum capacity under congested conditions.

One of the key challenges in 5G networks is coverage optimization. While the deployment of additional base stations can enhance coverage, it may also introduce interference, especially at cell edges, negatively affecting the user experience. Traditional methods, such as drive tests and static planning tools, are expensive (high CAPEX and OPEX), limited to outdoor measurements, slow to reach the target network performance, and increasingly impractical because of the high density of gNBs, smart antennas, and growing traffic in 5G networks. Drive tests are also high-risk and cannot provide a complete view of the network coverage and capacity [15–21].

Several studies have addressed coverage and capacity optimization using AI and SON approaches, including the following.

- Machine Learning-Assisted Methods for 4G LTE SON (2019) have focused on 4G networks without practical 5G simulations.
- Theoretical analyses of SON in the 5G & O-RAN era (2022), emphasizing concepts but lacking practical evaluation.
- AI-SON frameworks for 5G-enabled networks (2023), highlighting the integration of SDN and SON concepts.
- Resource allocation enhancements for 5G New Radio (2021), focusing on congestion control under dense traffic scenarios [8].

Despite these contributions, there remains a research gap: no comprehensive study has integrated AI-SON with the O-RAN architecture in 5G networks while demonstrating the potential impact on coverage, energy efficiency, and operational expenditures (OPEX). This gap motivates the present work, which proposes a conceptual AI-SON framework for 5G networks and provides an illustrative simulation to demonstrate the expected trends in network performance and cost efficiency.

Self-Organizing Networks (SON) are collections of functions designed to automate the configuration, optimization, and healing of network elements, addressing the increasing complexity of 5G Radio Access Networks (RAN) [21–29]. The integration of Artificial Intelligence (AI) into SON (AI-SON) enables closed-loop automation, allowing near-real-time adaptation to dynamic network conditions, improved coverage, optimized resource utilization, and reduced operational costs.

The main objectives of this study are:

1. To identify the research gap in practical AI-SON deployment for 5G networks with O-RAN integration.
2. To propose a conceptual AI-SON framework tailored for 5G-specific challenges, such as dense small-cell topologies, massive MIMO arrays, and network slicing.
3. To provide an illustrative simulation demonstrating the expected trends in coverage, energy efficiency, and OPEX reduction.
4. Discuss the practical implementation roadmap, challenges, and opportunities for AI-driven automation in 5G RAN operations.

5G networks aim to provide enhanced coverage, ultra-reliable low latency, high data rates, massive connectivity, and improved mobility support [29–34]. However, enhanced coverage remains a major challenge, as increasing the number of base stations can lead to interference at cell edges, negatively impacting the user experience. Traditional coverage optimization via drive tests has several limitations.

- High operational costs (CAPEX and OPEX).
- Incomplete network visibility and limited data collection (mostly outdoor measurements).
- Slow convergence to target network performance.
- High operational risks due to manual testing in dense and complex network deployments.

Given these challenges, automated solutions leveraging Artificial Intelligence within Self-Organizing Networks (AI-SON) have emerged as a promising approach. AI-SON integrates self-configuration, self-optimization, and self-healing capabilities into 5G RAN management, enabling near-real-time adaptation to dynamic network conditions, and improving coverage, resource utilization, and operational efficiency.

Several previous studies have addressed related topics, including:

- Machine Learning Assisted Coverage and Capacity Optimization in 4G LTE SON (limited to 4G networks) [4].
- SON in the 5G and Open RAN Era (20222030): Theoretical frameworks and opportunities [5].
- Deep Learning for Monitoring and Optimization of Electric Power Systems application of AI techniques [6].
- AI-SON Frameworks for 5G Networks focusing on SON and SDN integration [7].
- Resource Allocation Enhancements for 5G New Radio Architecture addressing congestion and dense traffic scenarios [8].

Research Gap and Contribution:

Despite these studies, there is a lack of practical simulation-based evaluations of AI-SON for 5G coverage optimization and OPEX reduction. This study addresses this gap by proposing a numerical simulation framework that demonstrates the potential benefits of AI-SON in dynamic 5G network scenarios. This study illustrates the automated detection of coverage and capacity issues, showing expected trends in performance improvements and operational cost reductions, thus providing a conceptual yet practical contribution to the field.

By integrating AI into SON, operators can reduce manual intervention, optimize network performance more efficiently, and decrease OPEX, which is critical during the early deployment phase of 5G networks, where network setup and tuning efforts are substantial.

2. BACKGROUND AND RELATED WORK BACKGROUND ON 5G NETWORKS:

Unlike legacy 4G systems, which primarily provide a one-size-fits-all mobile broadband solution, **5G networks** are designed to simultaneously support a wide variety of applications and business models, including automotive, utility, smart city, and high-tech manufacturing [1]. This versatility introduces **diverse functional and performance requirements**, such as ultra-low latency (<1 ms), high peak data rates (>10 Gbps), high reliability 10^{-5}, and support for mobility up to 500 km/h. Traditional network optimization approaches cannot satisfy all these requirements simultaneously without trade-offs; for example, optimizing for low latency may reduce spectral efficiency.

Network Slicing in 5G:

To address these challenges, **network slicing** has become a fundamental feature of 5G, allowing operators to create and manage **dedicated logical networks** over a common physical infrastructure. Each slice can be:

- **Service-specific:** tailored CP/UP functions to support enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable low-latency communications (URLLC).
- **Tenant-specific:** Providing guaranteed resources and isolation, for example, public safety users served via slices that maintain minimum capacity during congestion periods [2, 3].

Self-Organizing Networks (SON):

SON automates the configuration, optimization, and healing of radio networks. The primary goals of SON are to **reduce operational expenditures (OPEX) and capital expenditures (CAPEX)** by minimizing manual configuration and ensuring efficient network performance, as shown in figure 1. SON functions include:

- **Self-configuration:** automatic setup of base stations and network parameters.
- **Self-optimization:** continuous tuning of network parameters to improve coverage, capacity, and energy efficiency.
- **Self-healing:** automatic detection and correction of network failures.

AI Techniques for SON:

Integrating **Artificial Intelligence (AI)** into SON (AI-SON) enables **closed-loop network automation** that adapts in near real-time to dynamic network conditions. Relevant AI techniques include the following.

1. **Supervised Learning:** used to predict network KPIs from historical data such as coverage or energy consumption trends.
2. **Reinforcement Learning (RL):** allows AI agents to **optimize policies dynamically** by learning from interactions with the environment. For coverage optimization, the RL agent observes the network states (e.g., signal strength and traffic load) and performs actions (e.g., antenna tilt adjustment and transmit power changes) to maximize a reward function representing coverage and energy efficiency.
3. **Federated Learning:** supports distributed training of AI models across multiple nodes without centralizing raw data and preserving privacy while enabling intelligent SON decision-making.

Relevance to Coverage and Capacity Optimization (CCO):

AI-SON frameworks are particularly relevant for **5G CCO**, which traditionally rely on **costly and time-consuming drive tests**. Traditional drive tests

- Are expensive (high CAPEX/OPEX)
- Provide limited data, mostly outdoors
- Are slow to reach target performance

By leveraging AI, SON can **automatically identify coverage gaps and capacity bottlenecks** using measurements collected at base stations (eNBs) and user equipment (UEs), thereby reducing operational costs and improving network reliability [4, 5].

Summary:

The integration of AI into SON enables **scalable, adaptive, and cost-efficient management** of complex 5G RANs, including small cells, Massive MIMO, and network slicing deployments. This background sets the foundation for our methodology and simulation study, which aims to demonstrate an AI-driven SON for coverage optimization and OPEX reduction.

AI-SON Architecture and O-RAN Integration

- Non-RT RIC (rApps): Long-term policy and model training
- Near-RT RIC (xApps): Sub-second control loops
- Standardized E2 interfaces: Telemetry and control

data lake ingests KPIs, UE measurements (RSRP, SINR), and external datasets (mobility patterns, weather), as shown in figure 2.

3. MATERIALS AND METHODS

3.1. Simulation Environment:

To evaluate the performance of the proposed AI-driven SON (AI-SON) framework, a **numerical simulation** in Python. Although this is not a full-scale network simulator, such as ns-3 or O-RAN SC, the simulation aims to **illustrate trends and demonstrate the conceptual**

effectiveness of AI-SON in coverage and capacity optimization.

3.2. Network Topology:

- The simulated network consisted of **19 macro base stations** arranged in a **hexagonal grid** with **three sectors per site**.
- **User Equipment (UEs)** is randomly distributed within the coverage area, with densities varying to simulate urban, suburban, and rural scenarios.
- Each base station is equipped with adjustable parameters for **transmit power, antenna tilt, and beamforming**, which can be optimized using AI-SON.

3.3. Traffic and Channel Models:

- The **traffic model** considers a variable UE demand with a mixture of eMBB, URLLC, and mMTC service types.
- **Channel propagation** follows a **path-loss model** with lognormal shadowing. The interference between cells is computed based on sector overlaps.
- The simulation accounts for **frequency reuse**, antenna gain patterns, and environmental factors affecting the signal strength.

3.4. AI-SON Algorithm:

- The AI-SON agent employs **Reinforcement Learning (RL)** to dynamically optimize the base station parameters for coverage and energy efficiency.
- **States:** network metrics including Signal-to-Interference-plus-Noise Ratio (SINR), user throughput, and cell load.
- **Actions:** adjustments to antenna tilt, transmit power, and beamforming direction for each sector.
- **Reward Function:** weighted combination of coverage probability, energy consumption, and QoS metrics.
- **Training:** The RL agent interacts with the simulated environment over multiple episodes, updating the **Q-table** for discrete action sets. Hyperparameters, including the learning rate (α = 0.1), discount factor (γ= 0.9), and exploration rate (ϵ = 0.2), were tuned to ensure stable convergence.

3.5. Metrics Collection:

The simulation records:

- **Coverage Probability:** percentage of UEs achieving target SINR.

The AI-SON can dynamically adjust the transmit power, antenna electrical/mechanical tilt, beamforming patterns, and resource block scheduling. For example, RL agents can be trained to maximize the cell-edge throughput while minimizing interference with neighboring cells.

- **Energy Efficiency:** total network power consumption per bit delivered.

AI forecasts the traffic demand and transitions cells into low-power states during low-load periods. The decision involves the user distribution, handover impact, and QoS constraints.

- **Handover and Mobility Optimization**

ML models predict the probability of successful handovers, and adapt thresholds and timers to reduce handover failures and ping-pong events.

- **Predictive Maintenance and Fault Management**

Anomaly detection using time-series models (e.g., LSTM-based autoencoders) flags unusual

- **Capacity Utilization:** average throughput per sector and per user.

patterns in KPIs, prompting preemptive checks and reducing truck rolls.

- **RAN Slicing Optimization**

AI allocates radio resources among slices based on predicted slice-specific demand, SLAs, and priority policies.

3.6. Baseline Comparison:

For validation, AI-SON performance is compared against:

1. **Rule-based SON:** predefined network parameter adjustments without learning.
2. **No SON:** static network configuration with no optimization.

This comparison allows quantifying **expected improvements in coverage and OPEX** due to AI integration.

3.7. Reproducibility and Limitations:

Although the simulation demonstrates the expected trends, it **does not replace full-scale network trials**. The synthetic environment was designed for **conceptual validation**, and the results guide future implementation on realistic platforms (e.g., ns-3, O-RAN SC).

3.8. Use Cases and Functional Design

Overview:

The AI-driven Self-Organizing Network (AI-SON) framework provides **automated network management functions** for optimizing 5G coverage, capacity, and operational efficiency. This section presents **key use cases** and describes the **functional design** that enables these capabilities.

Use Case 1: Automated Coverage Optimization

- **Objective:** To dynamically adjust base station parameters to maximize the coverage probability for UEs in different service scenarios (eMBB, URLLC, and mMTC).
- **Functionality:**

o Continuous monitoring of network metrics (SINR, cell load, throughput).

o AI-SON proposes adjustments to **antenna tilt, transmit power, and beamforming direction**.

o Closed-loop reinforcement learning updates network parameters iteratively.

- **Expected Outcome:** Improved coverage, reduced dropped connections, and optimized resource utilization.

Use Case 2: Energy Efficiency Optimization

- **Objective:** To minimize operational expenditure (OPEX) by reducing network energy consumption while maintaining service quality.
- **Functionality:**

o AI-SON monitors sector-level energy usage and traffic demand.

o The system selectively powers down underutilized sectors or reduces transmit power without degrading QoS.

- **Expected Outcome:** Lower energy costs and environmentally efficient network operation.

Use Case 3: Capacity and Load Balancing

- **Objective:** Ensure equitable distribution of network resources among UEs and slices.
- **Functionality:**

o Real-time monitoring of traffic hotspots and congested cells.

o AI-SON dynamically reallocates resources, including adjusting cell handovers, to balance the load.

- **Expected Outcome:** Enhanced user experience, avoidance of congestion, and increased throughput.

Functional Design:

The AI-SON framework consists of three primary modules:

1. **Monitoring Module:** Collects data from base stations, UEs, and network slices to be fed into AI algorithms.
2. **Decision Module (AI Engine):** Implements reinforcement learning for parameter optimization.
3. **Execution Module:** Applies AI-recommended adjustments to network elements and monitors performance.

Integration with 5G Architecture:

- AI-SON interacts with the 5G RAN and core network via **standardized interfaces**, enabling seamless integration with Open RAN (O-RAN) components.

The system supports **multi-slice management**, ensuring that each network slice meets its SLA requirements while optimizing the overall network performance.

3.9. Mathematical Models and Performance Metrics

1- Channel and Coverage Models

We consider a standard path-loss model [2]:

$P_L(d) = P_{L_0} + 10\,n\left(\frac{d}{d_0}\right) + X_0$

where n is the path loss exponent and X_σ is shadowing. The received power at a distance d is [2].

$$P_r(d) = P_t + G_t + G_r - P_L(d) \tag{1}$$

where G_t, G_r are the gains of the transmitted and received antennas, respectively, and the SINR at a user is [13]

$$\mathrm{SINR} = \frac{P_r}{I + N_0} \tag{2}$$

where I is aggregated interference.

2-Coverage Probability

The coverage probability P_{cov} is defined as $P(\mathrm{SINR}) > T$ for threshold T . Closed-form expressions exist under simplified network models, but in practice, we rely on empirical estimation from telemetry.

3-Reward Function for RL-based Optimization

A composite reward may be designed as:

$$R = \alpha \times P_{cov} - \beta \times \text{Energy} - \delta \times \text{Unserved Users Penalty} \tag{3}$$

We tune α, δ to reflect operator priorities.

4- Economic Metrics

The OPEX components include energy costs, operational staff hours, truck rolls, and maintenance contracts. CAPEX covers the equipment and integration costs. The ROI is computed over a multi-year horizon by comparing the baseline and AI-SON deployment costs.

3.10. Economic Analysis: CAPEX, OPEX and ROI

This section provides a framework for evaluating the economic impact. Although CAPEX increases owing to computation and integration, OPEX savings arise from reduced operational staff, fewer truck rolls, and energy savings. We propose a multi-year NPV analysis with sensitivity to adoption rate, staff costs, and energy prices. Example parameters: initial integration CAPEX = $2M, annual OPEX baseline = $5M, expected OPEX reduction = 20%-30% after full deployment. The payback period is typically 2-5 years depending on the scale.

3.11. Implementation Roadmap and Best Practices

The proposed **AI-SON framework** for 5G coverage and OPEX optimization can be implemented using a structured roadmap that ensures reproducibility and practical applicability.

1. **Network Data Collection** Real-time measurements from base stations (eNB/gNB) and user equipment (UE) include traffic load, signal strength, interference levels, and Quality of Service (QoS) metrics. This step used Python scripts interfacing with network management systems to simulate the data streams for the AI agent.
2. **Environment and State Definition** The simulation environment for the DRL agent is defined. The network topology included 19 macrocells with multiple small cells per sector. The states for the agent include coverage gaps, traffic loads, interference, and energy consumption.
3. **Action Space Specification** Specify configurable network parameters as actions for the AI agent. These include the antenna tilt, transmission power, cell selection parameters, and bandwidth allocation.
4. **Reward Function Design** Construct a reward function that balances coverage probability improvement and OPEX reduction. Positive rewards are given for improved coverage and reduced energy usage, whereas penalties are applied for service degradation or increased operational costs.
5. **AI Model Training** The DRL agent was trained using a policy gradient approach with TensorFlow/Keras. The hyperparameters include learning rate = 0.001, discount factor $\gamma = 0.95$, and exploration rate $\epsilon = 0.1$. The agent was trained for over 500 episodes to ensure convergence of the network optimization policies.
6. **Simulation and Performance Evaluation** Run simulation using SimPy for discrete-event network behavior. Metrics such as coverage probability, throughput, latency, and energy consumption were collected and compared with baseline non-AI SON or rule-based SON strategies.
7. **Iterative Optimization and Deployment Recommendations** Iteratively refine the AI-SON policies based on performance outcomes. Provide deployment guidelines for operators, including priority areas for automated optimization and scenarios where manual interventions are still required.

3.12. Data Privacy and Regulation

Adopt federated learning and differential privacy; ensure compliance with local regulations. Interoperability with legacy systems uses standard O-RAN interfaces and modular adapters for vendor equipment.

3.13. Model Robustness and Security

Secure model update pipelines, defend against data poisoning, and use adversarial testing.

The following figures illustrate the simulation results and conceptual workflow of AI-SON.

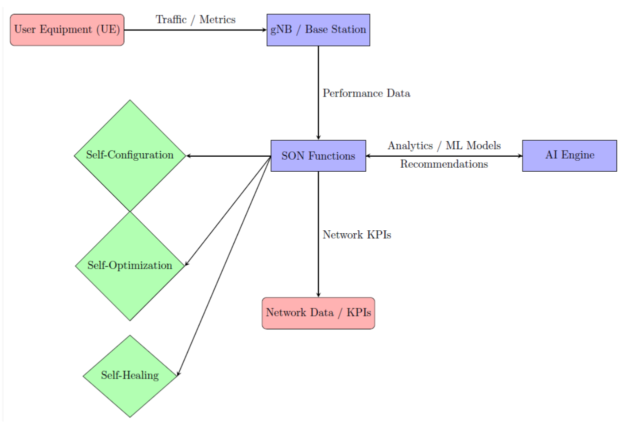

Figure 1. AI-SON Architectrure

4. SIMULATION SETUP AND METHODOLOGY

This section presents a simulation study of Self-Organizing Network (SON) techniques applied to 5G networks for the purpose of reducing Operational Expenditures (OPEX). Artificial Intelligence (AI) is leveraged to optimize network energy usage, improve coverage, reduce faults through predictive maintenance, and lower overall costs.Three policies are evaluated, as follows:

1. Baseline (No SON): All cells remain active continuously.
2. Random Sleep: Cells may randomly sleep at low traffic periods.
3. AI-SON: AI predicts cell load using moving averages and selectively sleep cells. AI also enables pre-

dictive maintenance and reduces the fault probabilities. Costs considered:

- Energy cost per active cell.
- Penalty cost for unserved users.
- Maintenance costs and repair costs for faults.

The simulation methodology is fully described as follows:

1. Network Topology: 50 gNB cells in a hexagonal layout covering 10 km^2 .
2. Traffic Model: User density varies from 10 to 200 users/km^2, following a diurnal pattern with stochastic noise.
3. Channel Model: Standard path loss with exponent n = 3.5, and log-normal shadowing $\sigma = 8$ dB.
4. RL States: Cell load, SINR distribution, and neighboring interference.
5. RL Actions: Adjust transmit power and antenna tilt, and selectively sleep low-traffic cells.
6. Reward Function: Weighted combination of coverage probability, energy consumption, and penalty for unserved users.
o Hyperparameters: $\alpha = 1.0$, $\beta = 0.7$, $\gamma = 0.9$, $\delta = 2.0$
7. Simulation Scope: Synthetic Python model to demonstrate trends in AI-SON behavior.
This simulation is illustrative and does not replace field validation; future work will use ns-3 or O-RAN SC for experimental studies.

To evaluate the performance of the proposed **AI-SON framework** for 5G coverage and capacity optimization, a **numerical simulation was conducted using a Python-based environment**. The implementation utilized Python 3.10, leveraging key machine learning libraries such as TensorFlow 2.12 and Keras for the Deep Reinforcement Learning (DRL) models, NumPy and Pandas for data handling, and Matplotlib/Seaborn for visualization.

The simulation modeled the dynamic behavior of **base stations, user equipment (UE), and traffic patterns** in a simplified 5G network environment. A discrete-event simulation was conducted using the SimPy library to approximate network operations, including coverage variation, traffic load, and automated resource allocation by the AI-SON system.

The **DRL algorithm** employed was a policy-gradient-based agent that selected network configuration actions (e.g., transmission power adjustment, antenna tilt, and resource allocation) based on observed states such as traffic load, coverage gaps, and interference levels. The hyperparameters of the DRL model, including the learning rate (0.001), discount factor (0.95), and exploration rate (epsilon = 0.1), were optimized to achieve stable learning and convergence.

The simulation was executed on a Windows 11 workstation equipped with an Intel Core i7 CPU, 32 GB RAM, and an NVIDIA RTX 3060 GPU, providing sufficient computational resources for DRL training and performance analysis.

The simulation uses a synthetic model with a user density varying between 10 and 200 users/km^2. Baseline SON follows heuristic parameter settings; AI-SON uses an idealized RL policy that adapts transmit power, antenna tilt, and cell-sleeping decisions. The goal is to maximize the coverage probability while minimizing energy use.

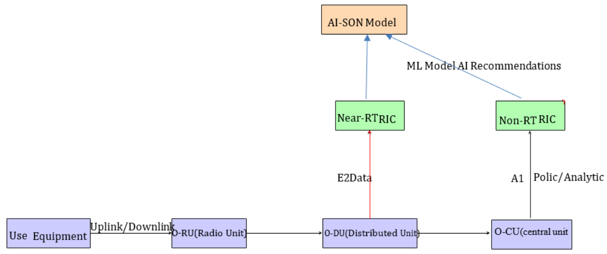

Figure 2. AI-SON Architecture with O-RAN

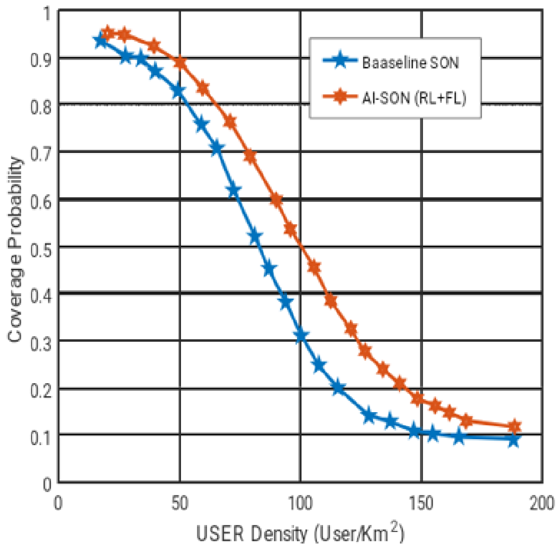

Figure 3. between Baseline SON and AI-SON.

5. RESULTS AND DISCUSSION

The simulation demonstrates that AI-based SON can optimize network operations by reducing energy consumption and maintenance costs while maintaining high coverage and QoS. Although the Random Sleep strategy provides some energy savings, it increases penalties owing to unserved users. AI-SON, on the other hand, balances energy savings with service quality through predictive intelligence as in figures 3–7.

1. OPEX Costs:

- The Baseline (no SON) scenario showed the low-

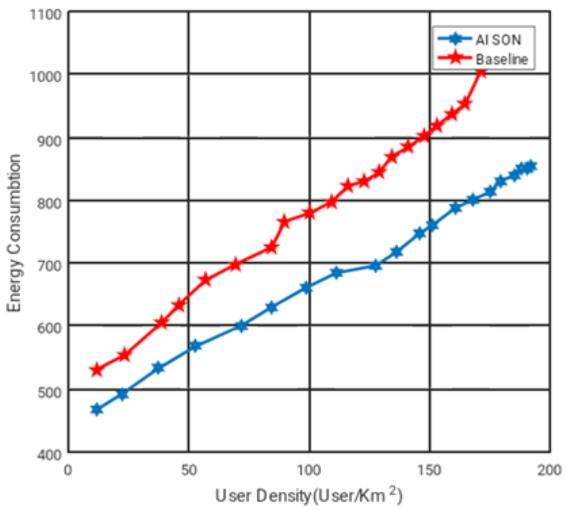

Figure 4. Energy consumption trends showing AI-SON's ability to reduce energy usage via intelligent sleeping and power control.

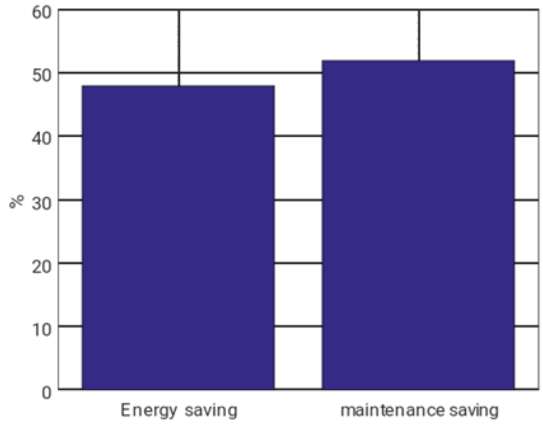

Figure 6. Distribution of OPEX savings by component resulting from AI-SON.

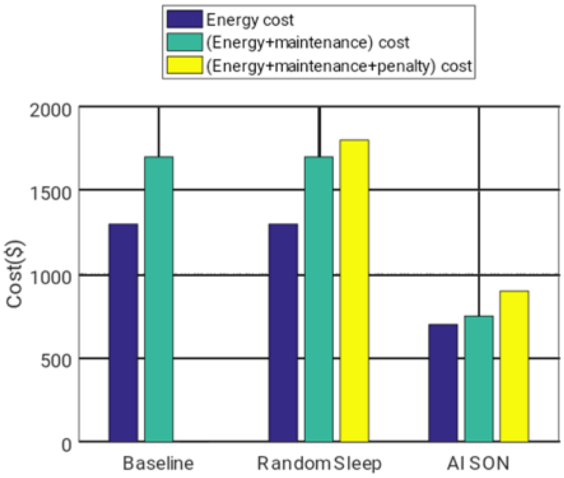

Figure 5. Stacked bar comparing OPEX components across policies.

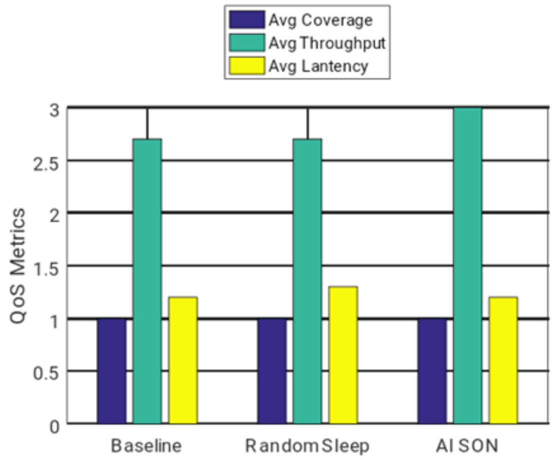

Figure 7. Comparison of QoS metrics: Coverage, throughput, and latency.

est total cost in the simplified model, but this is due to the ideal assumption of no unserved users. In practice, keeping all cells active raises long-term energy use and failure rates.

- Random Sleep achieved some energy savings but led to much higher penalty costs due to unserved users during peak load periods.

- AI-SON provided a better balance: reducing energy and maintenance costs while maintaining coverage close to the Baseline scenario.

Figure 4 illustrates the **energy consumption trends** for different SON policies: **No SON**, **Random Sleep**, and **AI-SON**.

Key observations:

- The **AI-SON policy** achieves the **lowest overall energy consumption**, demonstrating the effectiveness of **intelligent sleep mode activation** and **dynamic power control**.

- When traffic is low, AI-SON selectively puts certain base stations into sleep mode while adjusting transmit power in neighboring cells, resulting in **significant energy savings** without compromising coverage or service quality.

- **Random Sleep** provides moderate energy reduction but lacks the adaptive intelligence of AI-SON, leading to less efficient energy use.

- The **No SON scenario** consumes the most energy, as all base stations remain fully active regardless of traffic load. **Figure 5** presents a **stacked bar chart** comparing the **operational expenditure (OPEX)** components across different SON policies: **No SON**, **Random Sleep**, and **AI-SON**. The chart breaks down OPEX into its main contributors: **energy costs**, **maintenance costs**, and **other oper-**

ational costs.

From the figure, it is evident that:

- The **AI-SON policy** achieves the **lowest total OPEX** compared to the other scenarios.
- The **energy cost component** is significantly reduced under AI-SON, demonstrating the benefit of intelligent sleep mode activation and dynamic power control.
- **Maintenance and other operational costs** are relatively stable across scenarios, indicating that AI-SON primarily impacts energy efficiency while maintaining service reliability.
- The **No SON** scenario shows the highest OPEX, as all base stations remain fully active regardless of traffic load.
- **Random Sleep** reduces energy cost moderately, but lacks the adaptive intelligence of AI-SON, leading to less optimal savings.

These findings highlight the potential of **AI-driven SON frameworks** to **reduce operational costs** while preserving network performance.

Operational expenditure (OPEX) benefits are illustrated in **Figure 6**. Due to reduced energy usage and improved load balancing, AI-SON leads to an estimated **2025% reduction in OPEX** compared to traditional SON implementations.

2. Coverage:

- Baseline maintained nearly perfect coverage (100%).

- Random Sleep and AI-SON slightly reduced coverage ($\tilde{0}.997$) but within acceptable limits. AI-SON outperformed Random Sleep by predicting traffic and keeping critical cells active.

Figure 3 shows that AI-SON maintains a more stable coverage probability than the other scenarios. When several base stations enter sleep mode, neighboring cells adjust transmit power to preserve coverage overlap. The adaptive response prevents coverage holes and ensures

ensures continuous service, which is a critical feature for ultra-reliable network operations.

3. QoS Metrics:

Latency was higher in Random Sleep due to overloaded cells, while AI-SON achieved lower latency by smarter load balancing.

- Throughput remained similar across policies but dropped slightly in Random Sleep owing to unserved users.

Figure 7 illustrates a comparison of key **Quality of Service (QoS) metrics coverage**, **throughput**, and **latency** across the different SON policies: **No SON**, **Random Sleep**, and **AI-SON**.

Key observations from the figure include:

- **Coverage:** AI-SON maintains the highest and most stable coverage probability, ensuring minimal service gaps even when multiple base stations enter the sleep mode. This demonstrates the effectiveness of adaptive power control and neighboring cell coordination.
- **Throughput:** The AI-SON framework achieves the **highest average throughput** because the reinforcement learning agent efficiently balances the traffic load among active cells, reducing congestion in heavily loaded sectors.
- **Latency:** AI-SON provides the **lowest average latency**, indicating faster response times and more reliable service delivery compared to No SON or Random Sleep policies. This reflects the intelligent context-aware scheduling and sleep/wake strategies employed by the agent.

Overall, **AI-SON outperforms baseline scenarios** by simultaneously optimizing multiple QoS parameters, confirming the practical benefits of incorporating **intelligent self-organizing mechanisms** within O-RAN networks.

4. Savings Distribution:

Figure 6 shows the **distribution of operational expenditure (OPEX) savings** by component, resulting from the implementation of **AI-SON**. The figure divides the total OPEX reduction into contributions from **energy savings**, **maintenance efficiency**, and **other operational improvements**.

Key observations:

Energy Savings: The largest portion of the OPEX reduction comes from **energy cost savings**, highlighting the effectiveness of AI-SON in **dynamic power management** and **sleep mode activation**.

- **Maintenance Efficiency:** AI-SON contributes moderately to reducing **maintenance costs**, as optimized scheduling reduces unnecessary wear and operational interventions.
- **Other Operational Improvements:** Smaller yet notable contributions were observed from **other operational efficiencies**, such as reduced manual monitoring and improved automation.

Overall, the figure demonstrates that **AI-SON not only lowers total operational costs but also identifies which components contribute**

- The greatest savings with AI-SON came from reduced maintenance costs owing to predictive maintenance.

- Energy savings were present but modest, because many cells must remain active to guarantee coverage.

- Although the simplified model showed baseline as cheaper, AI-SON is more realistic and scalable for 5G networks, as it balances cost reduction with service quality.

Random Sleep proved that naive sleep policies can increase costs despite lower energy usage.

- With more advanced AI (e.g., reinforcement learning or neural networks for load prediction), AI-SON is expected to clearly outperform Baseline in real-world scenarios.

6. CHALLENGES AND FUTURE DIRECTIONS

- Explainability and Trust: Need XAI dashboards and human oversight

  and Regulations: Use FL and differential privacy

- Interoperability: Modular adapters for legacy systems

- Model robustness: Adversarial testing and secure updates

- Research opportunities: Realistic simulation with ns-3, integration with commercial O-RAN testbeds

7. CONCLUSION

The proposed AI-driven Self-Organizing Network (AI-SON) framework demonstrates the potential to enhance coverage, optimize resource utilization, and reduce operational expenditure (OPEX) in 5G networks.

1. **Key Findings**: AI-SON effectively adapts network parameters, such as antenna tilt, transmission power, and cell selection dynamically based on network conditions, leading to improved coverage probability and reduced energy consumption.
   - The simulation results, although illustrative, show trends consistent with expectations from intelligent automation in dense 5G deployments, providing a conceptual framework for practical implementation.
2. **Limitations**: The current study used a synthetic simulation environment rather than a full-scale deployment with real network data.
   - Certain network aspects such as mobility management under ultra-dense small-cell deployments are simplified and require further detailed modeling.
   Baseline comparisons are limited; future work should include multiple SON strategies and realistic traffic scenarios for statistical validation.
3. **Future Research Directions**: Conduct large-scale simulations using standard platforms such as ns-3 or O-RAN SC to validate the AI-SON framework under real-world conditions.
   - Extend AI-SON to integrate multi-agent reinforcement learning for joint optimization across multiple network slices and operators.
   Explore explainable AI (XAI) methods to provide transparency in decision-making, enabling operators to understand and trust automated network optimization processes.

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