

Adaptive Multi-Objective Optimization Framework for 5G-Enabled IoT Networks: Enhancing Performance and Energy Efficiency in Smart Application Environments

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إطار عمل مُحسِنٍ متعدد الأهداف تكيفي لشبكات إنترنت الأشياء المُمكنة بتقنية الجيل الخامس: تعزيز الأداء وكفاءة الطاقة في بيئات التطبيقات الذكية

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Abstract:

The convergence of fifth generation (5G) networks and the Internet of Things (IoT) is composed to revolutionize smart application environments, such as smart cities and industrial automation. However, this integration introduces significant challenges, primarily the conflicting demands of maximizing network performance (e.g., throughput, latency) and minimizing energy consumption, which is projected to surge with hyper-dense deployments. This paper proposes a novel Adaptive Multi-Objective Optimization (AMOO) framework designed to address this trade-off in 5G-enabled IoT networks. The framework leverages machine learning to dynamically adapt optimization strategies based on real-time network conditions and traffic patterns. We formulate a multi-objective problem to simultaneously optimize spectral efficiency (SE) and energy efficiency (EE). The core of our framework is an AI-enhanced Non-Dominated Sorting Genetic Algorithm (AI-NSGA), which intelligently explores the solution space for resource allocation, including power control and small cell activation. Simulation results, modeled in a MATLAB environment, demonstrate that our proposed AMOO framework achieves a superior Pareto front compared to static optimization and single-objective approaches. It goes along with substantial energy savings up to 25% in our scenarios while maintaining high Quality of Service (QoS) levels, providing a scalable and efficient solution for sustainable smart city and Industrial IoT (IIoT) deployments.

Keywords: 5G, Internet of Things (IoT), Multi-Objective Optimization, Energy Efficiency, Spectral Efficiency, Adaptive Resource Allocation, Machine Learning, Smart Cities.

المخلص

يهدف التكامل بين شبكات الجيل الخامس (5G) وإنترنت الأشياء (IoT) إلى إحداث ثورة في بيئات التطبيقات الذكية، مثل المدن الذكية والأتمتة الصناعية. ومع ذلك، فإن هذا التكامل يطرح تحديات كبيرة، في المقام الأول التضارب بين متطلبات زيادة أداء الشبكة (مثل معدل نقل البيانات وزمن التأخير) وتقليل استهلاك الطاقة، والذي من المتوقع أن يرتفع بشكل كبير

مع عمليات النشر عالية الكثافة. تقترح هذه الورقة إطار عمل جديد للتحسين التكيفي متعدد الأهداف (AMOO) مصمم لمعالجة هذه المفاضلة في شبكات إنترنت الأشياء التي تدعم الجيل الخامس. يستفيد إطار العمل من التعلم الآلي للتكيف ديناميكياً مع استراتيجيات التحسين بناءً على ظروف الشبكة وأنماط حركة المرور في الوقت الفعلي. نقوم بصياغة مشكلة متعددة الأهداف لتحسين كفاءة الطيف (SE) وكفاءة الطاقة (EE) في وقت واحد. جوهر إطار العمل لدينا هو خوارزمية جينية غير مهيمنة معززة بالذكاء الاصطناعي (AI-NSGA)، والتي تستكشف بكفاءة مساحة الحلول لتخصيص الموارد، بما في ذلك التحكم في الطاقة وتفعيل الخلايا الصغيرة. تُظهر نتائج المحاكاة، التي تم نمذجتها في بيئة (MATLAB) أن إطار عمل المقترح (AMOO) يحقق واجهة باريتو متفوقة مقارنة بالتحسين الثابت والنهج أحادية الهدف. ويصاحب ذلك توفير كبير في الطاقة يصل إلى 25٪ في سيناريوهاتنا مع الحفاظ على مستويات عالية من جودة الخدمة (QoS) مما يوفر حلاً قابلاً للتطوير وفعالاً للمدن الذكية المستدامة ونشر إنترنت الأشياء الصناعية (IoT).

الكلمات المفتاحية: الجيل الخامس، إنترنت الأشياء (IoT)، التحسين متعدد الأهداف، كفاءة الطاقة، الكفاءة الطيفية، تخصيص الموارد التكيفي، التعلم الآلي، المدن الذكية.

Introduction

The Internet of Things (IoT) and fifth-generation (5G) wireless technology are revolutionary forces that are changing contemporary computer and communication [23]. In order to accommodate a large number of connected devices, provide ultra-reliable low-latency communication (URLLC), and supply enhanced mobile broadband (eMBB), 5G networks are a paradigm leap rather than just a gradual improvement over 4G/LTE [27]. In complex ecosystems like smart cities, where billions of sensors and gadgets need flawless communication, 5G is therefore a crucial enabler for the full-scale deployment of the Internet of Things [8], [5]. Smart grids, healthcare, and intelligent transportation systems are just a few of the urban services that 5G and IoT integration promises to improve [12], [27].

But there is a price for this unparalleled connectedness. Energy consumption significantly increases as a result of the hyper-dense deployment of network infrastructure, particularly small cells (SCs) required to provide coverage and capacity for huge IoT [1]. According to projections, if 5G infrastructure is not adequately optimized, it might need two to three times as much power as 4G networks [6]. This energy footprint runs opposed to the objectives of "green communication" and presents a significant challenge to network operators' sustainability and operational expenditure (OPEX) [17], [16]. A complicated resource allocation issue is also brought about by the varied needs of different IoT applications, which range from high-bandwidth video surveillance to low-power, low-data-rate sensors. It is a challenging challenge to manage these resources in order to minimize energy efficiency (EE) and maximize network performance indicators such as spectral efficiency (SE) [24], [25].

These goals frequently clash; for example, raising transmission power to enhance data rates and SE directly raises energy usage, which lowers EE [24]. For these complicated situations, single-objective optimization techniques that concentrate just on performance or energy savings are insufficient [14]. A multi-objective optimization (MOO) method that can examine the trade-offs and provide a set of ideal solutions (the Pareto front) is therefore required [4]. Furthermore, such a framework must be flexible due to the dynamic nature of IoT environments, which include varying traffic volumes and shifting channel circumstances. As the network state changes, a static optimization method will soon become less effective. Thus, sustained efficiency requires an adaptive framework that can learn from the environment and modify its parameters in real-time [30], [28].

An Adaptive Multi-Objective Optimization (AMOO) framework for 5G-enabled IoT networks is proposed in this paper to address these issues. Our main contributions are:

1. A thorough formulation of the joint optimization of energy and spectrum efficiency as a multi-objective problem designed for dense IoT installations in smart cities.
2. The creation of an adaptive optimization method that forecasts network states to direct the optimization process by combining machine learning (ML) and a Non-Dominated Sorting Genetic method (NSGA).
3. A thorough simulation-based assessment of the suggested framework that shows how it outperforms traditional static and single-objective techniques in attaining a balanced and effective network operation. This is how the rest of the paper is structured.

A theoretical overview of multi-objective optimization and a survey of pertinent literature are given in Section 2. The suggested system model, problem formulation, and adaptive optimization technique are described in depth in Section 3. The simulation results are shown and examined in Section 4. The paper is finally concluded in Section 5, which also offers recommendations for further research.

2. Literature Review And Theoretical Background

This section explores the fundamental ideas of adaptive networking and multi-objective optimization that form the basis of our approach. A thorough literature evaluation that places our approach within the current state-of-the-art research on resource management in 5G and IoT systems comes next.

2.1 Wireless Network Multi-Objective Optimization

Resource allocation in wireless networks is one of several real-world engineering challenges that require the simultaneous optimization of several, frequently incompatible goals. Multi-Objective Optimization (MOO) strives to identify a group of solutions that represent the greatest feasible trade-offs among the objectives, in contrast to single-objective optimization, which looks for a single optimal solution. If no target can be achieved without compromising at least one other aim, the solution is said to be Pareto optimum. The Pareto front is the collection of all such solutions [4].

Optimizing throughput, minimizing latency, optimizing spectral efficiency (SE), and minimizing energy consumption (or maximizing energy efficiency, EE) are frequent goals in the context of 5G/IoT [3], [26]. A multi-objective optimization problem (MOP) can be stated formally as follows:

$$\text{Minimize } F(x) = [f_1(x), f_2(x), \dots, f_k(x)]^T \quad (1)$$

subject to $x \in \Omega$, where Ω is the viable solution space, $f_i(x)$ are the k objective functions, and x is the vector of decision factors (such as power levels and sub-channel assignments). Because they can produce a well-distributed set of Pareto optimal solutions in a single run, evolutionary algorithms like the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) are frequently employed to solve MOPs [4].

2.2 Machine Learning and Adaptive Resource Management

Static resource allocation systems are ineffective in 5G IoT environments due to their extremely dynamic nature, which is marked by varying user density, mobility, and various application needs. In order to maintain optimal performance, adaptive resource management seeks to dynamically modify network parameters in response to shifting circumstances [18]. Artificial intelligence (AI) and machine learning (ML) have recently become effective technologies for facilitating this adaptability [25], [26].

In order to forecast future conditions like traffic load, user mobility patterns, and channel quality, machine learning models can be trained on both historical and current network data [28]. Network resources can then be proactively reconfigured using these forecasts. For example, intelligent agents that learn optimal resource allocation rules through interaction with the network environment can be developed using Reinforcement Learning (RL) approaches such as Q-learning, which do not require an explicit system model [15]. In order to manage the complexity of hyper-dense 5G networks, such data-driven techniques are essential [3], [29].

2.3 Review of Literature

Optimizing resource distribution in 5G and IoT networks has been the subject of extensive research. Single-objective optimization was a common topic of early research. Wang et al. [16], for instance, examined resource allocation in NOMA systems from the standpoint of energy efficiency. However, a move toward multi-objective techniques was required due to the inherent trade-offs in network performance.

In this field, Chi et al. have made significant contributions. They formulated the problem as an integer programming problem and proposed a multi-objective optimization strategy for the allocation of green tiny cells in smart cities [1], [3]. In order to obtain near-optimal solutions for the same problem while lowering computational costs, they subsequently presented an inventive Integer-based Non-Dominated Sorting Genetic Algorithm (I-NSGA) [4]. In a similar vein, Haile et al. [3] emphasized the significance of leveraging real-world data to direct optimization by proposing a data-driven Multi objective optimization framework for hyper-dense 5G network planning. Although they frequently rely on less-adaptive optimization models, these investigations validate the usefulness of MOO for balancing competing objectives.

Energy efficiency (EE) has been a major focus due to the push for "green" communications. To precisely capture and optimize the energy usage of 5G base stations, a number of research has put forth mathematical models [20], [22]. For the EE of CSMA-NOMA random access networks, a crucial technology for the enormous Internet of Things, Cao et al. [21] created comprehensive mathematical models and suggested optimization techniques to address the challenging non-convex problem. A major subject has been the trade-off between EE and spectral efficiency (SE), with research examining this relationship in a variety of settings. Such as ultra-dense networks

[26] and huge MIMO systems [24]. Taking into account the stochastic character of packet transmissions, Alam et al. [25] proposed a joint optimization of energy and spectral efficiency in heterogeneous networks.

In more recent times, intelligent and adaptive network management has been acknowledged as being made possible by the incorporation of AI/ML. A thorough analysis of the integration of AI, ML, and even Large Language Models (LLMs) in 5G/6G networks was presented by Usman et al. [18], highlighting its potential for resource efficiency. With an emphasis on methods for dynamic resource management, [28] examined the application of ML for resource optimization in upcoming wireless networks. Particular uses include federated reinforcement learning to optimize EE while maintaining data privacy [32] and AI-driven Discontinuous Reception (DRX) to control user equipment energy consumption [15]. By enabling real-time, context-aware decision-making, these AI-driven techniques promise to overcome the drawbacks of conventional optimization. For instance, adaptive frameworks utilizing reinforcement learning have been created for dynamic power allocation [30], and Q-learning has been suggested for real-time energy and network resource management in 5G-IoT systems [15].

This strong base serves as the basis for our efforts. Although MOO [1], [3] and AI-driven adaptability [18], [28] have been studied independently in the past, our framework is the first to combine these two ideas. In order to provide a more reliable and dynamic solution for 5G-enabled IoT networks, we provide an AI-enhanced MOO algorithm that not only identifies Pareto-optimal solutions for the EE-SE trade-off but also modifies its search strategy depending on ML-driven predictions about the network environment.

3. Adaptive Multi-Objective Optimization Framework Suggested

The practical elements of our suggested AMOO framework are presented in this section. The system model is described first, followed by the formulation of the multi-objective optimization problem and the description of the AI-enhanced adaptive algorithm that is intended to solve it.

3.1 Model of System

As shown in Figure 1, we examine the implementation of a heterogeneous network (HetNet) in an urban smart city setting. A group of M small cells (SCs), represented by $\mathcal{K} = \{1, 2, \dots, M\}$, deployed to support a high density of N IoT devices, represented by $\mathcal{U} = \{1, 2, \dots, N\}$, and a single Macro Base Station (MBS) offering umbrella coverage make up the network. IoT devices, such as smart meters, traffic sensors, and surveillance cameras, represent various smart city applications and have a variety of QoS needs.

A central controller, which may be installed on a Multi-Access Edge Computing (MEC) server or co-located with the MBS, oversees the distribution of resources [31]. The AMOO algorithm is carried out by this controller. Among the decision-making factors are:

- User Association Matrix (A): This is a binary matrix with $a_{nm} = 1$ if IoT device n is connected to SC m and 0 otherwise.
- Power Allocation Vector (P): The transmission power allotted to device n is represented by the vector p_n .
- SC Activity Vector (S): A binary vector with a value of 0 while the SC is in low-power sleep mode and 1 when it is active.

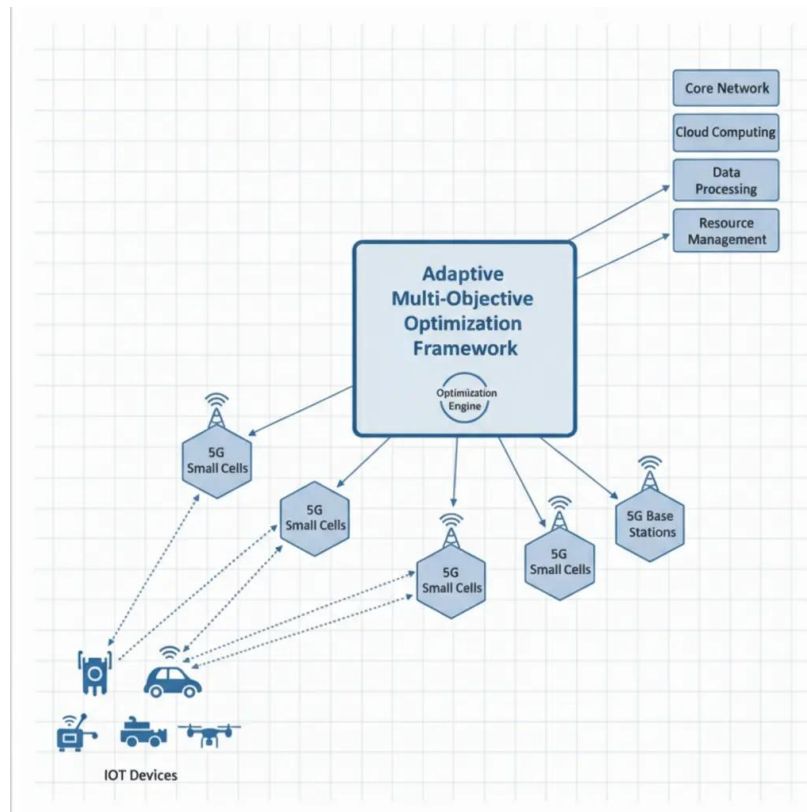


Figure. 1. Proposed 5G-Enabled IoT Network Architecture with Adaptive Optimization.

3.2 Formulation of Problems

Our methodology is based on a multiobjective optimization problem that aims to determine the best possible balance between energy efficiency and spectrum efficiency. The following is how the two goals are stated:

- 1) **The first goal is to maximize spectral efficiency (SE).**

Spectral efficiency quantifies how well data is transmitted using the available spectrum. The data rate R_n for an IoT device n linked to SC m is determined by the Shannon-

$$\text{Hartley theorem [23]: } R_n = B \log_2(1 + \text{SINR}_n) \quad (2),$$

where B is the channel bandwidth and SINR_n is the Signal-to-Interference-plus-Noise Ratio for device n . The aggregate of each device's rate determines the overall network throughput. The total throughput divided by the total bandwidth utilized yields the overall spectral efficiency. Our primary goal is to maximize the network as a whole.

$$\text{SE: Optimize } f_1(A, P) = \sum_{n=1}^N \sum_{m=1}^M R_n \quad (3).$$

- 2) **Goal 2: Reducing Total Energy Use**

The ratio of total data rate to total power usage is known as energy efficiency. Our goal is to minimize P_{total} , the total power usage, in order to optimize EE. The power consumption model incorporates both static and dynamic elements and is derived from [20]:

$$P_{\text{total}} = \sum_{m=1}^M (P_{m,\text{static}} + \Delta p \cdot \sum_{n=1}^N p_{n,m}) + \sum_{m=1}^M (1 - s_m) P_{m,\text{sleep}} \quad (4),$$

where p_n is the transmission power of device n , $P_{m,\text{static}}$ is the static power used by an active SC m , Δp is a coefficient associated with the power amplifier efficiency, and $P_{m,\text{sleep}}$ is the power used by a SC in sleep mode. Thus, our second goal is:

$$\text{Reduce } f_2(A, P, S) = P_{\text{total}} \quad (5).$$

3.3 Multi-Objective Issue

Finding the choice variables (A , P , and S) that solve the following is the full multi-objective optimization problem:

$$\text{Maximize } \{f1(A,P), -f2(A,P,S)\} \quad (6)$$

while taking into account power and QoS limitations for SCs and devices, such as minimum data rate.

3.4 The Algorithm for AI-Enhanced Adaptive NSGA (AI-NSGA)

We suggest an AI-enhanced NSGA, which we refer to as AI-NSGA, to solve the MOP given in (6). In order to adapt to the dynamic network environment, this approach incorporates a machine learning model into the NSGA-II algorithm's evolutionary process [4].

1. **Network State Prediction Using Machine Learning:** Using historical network data, such as traffic load per cell, the number of active users, and channel quality indicators, an LSTM neural network is trained offline. The MEC controller uses the trained LSTM model to forecast the network status for the upcoming time interval. Expected traffic demand and interference levels, which are crucial for resource allocation, are included in the forecast. Research on ML-based adaptive resource allocation served as the inspiration for this strategy [28].
2. **Adaptive NSGA-II:** To move a population of solutions closer to the Pareto front, the typical NSGA-II algorithm uses selection, crossover, and mutation. This procedure is improved by our AI-NSGA in the following ways:
 - **Intelligent Population Initialization:** A fraction of the first solutions is produced based on the LSTM model's predictions, as opposed to a completely random beginning population. For instance, first solutions will give priority to activating SCs in a particular area if heavy traffic is anticipated there.
 - **Adaptive Crossover and Mutation:** There is no set probability of crossover or mutation. They are dynamically modified according to the algorithm's convergence progress and the anticipated network state. To take advantage of good solutions, the mutation rate is reduced under projected stable network conditions. It is increased to investigate new areas of the solution space under anticipated dynamic conditions. The improvement in the quality of the Pareto front serves as the "reward" for this adaptive mechanism, which is a type of reinforcement learning [30].

The AMOO framework's general workflow is as follows:

1. **Data Collection:** Real-time data on network traffic, device locations, and channel conditions are continuously gathered by the MEC controller.
2. **State Prediction:** In order to forecast the network state for the next optimization cycle, the LSTM model analyzes the data.
3. **Adaptive Optimization:** The AI-NSGA algorithm is used. It intelligently initializes its population and modifies its genetic operators using the projected state as input.
4. **Solution Selection and Deployment:** Based on its present policy, the network operator can choose a solution from the resultant Pareto front (e.g., prioritizing energy savings during off-peak hours or optimizing performance during peak hours). The network is then set up with the matching resource allocation configuration (A, P, and S).
5. **Feedback Loop:** A closed-loop adaptive system is created by continuously retraining and improving the LSTM prediction model using data from the deployed solution's performance monitoring.

4. Performance Analysis and Simulation

We created a MATLAB simulation environment to verify the efficacy of our suggested AMOO framework. We simulated a 1 km² urban environment with 20 SCs dispersed at random and one MBS at the center. The traffic demands of the 200 IoT devices that were installed varied.

4.1 Configuring the Simulation

Table 1 provides a summary of the important simulation parameters. Three baseline algorithms were used to compare the performance of our suggested AI-NSGA:

- **Energy-Only Optimization (EE-Only):** An algorithm with a single target that just seeks to reduce overall energy usage (Equation 5).
- **Performance-Only Optimization (SE-Only):** Equation 3 describes a single-objective method that solely seeks to maximize spectral efficiency.
- **Static MOO (S-NSGA):** An AI-based adaptive mechanism is absent from this standard NSGA-II method, which has fixed parameters.

Table 1: Summary of the important simulation parameters

Parameter	Value
Simulation Area	1 km x 1 km
Number of SCs	20
Number of IoT Devices	200
Bandwidth	20 MHz
SC Max Transmit Power	24 dBm
IoT Device Max Transmit Power	20 dBm
SC Static Power (P_{static})	6.8 W [20]
SC Sleep Power (P_{sleep})	4.3 W [20]
Noise Power Spectral Density	-174 dBm/Hz
NSGA Population Size	100
NSGA Generations	200

4.2 Findings and Evaluation

The Pareto fronts produced by the static S-NSGA and AI-NSGA algorithms are displayed in Fig. 2. An ideal trade-off between total network throughput (a measure of SE) and total power consumption is represented by each point on the curve. Since the single-objective EE-Only and SE-Only algorithms yield a single solution, their fronts are represented by single points. Our adaptive method achieves higher throughput for each given level of power consumption and needs less power for any given throughput since the Pareto front of AI-NSGA clearly dominates that of S-NSGA. This illustrates the advantage of the machine learning-based adaptation, which directs the search to better areas of the solution space.

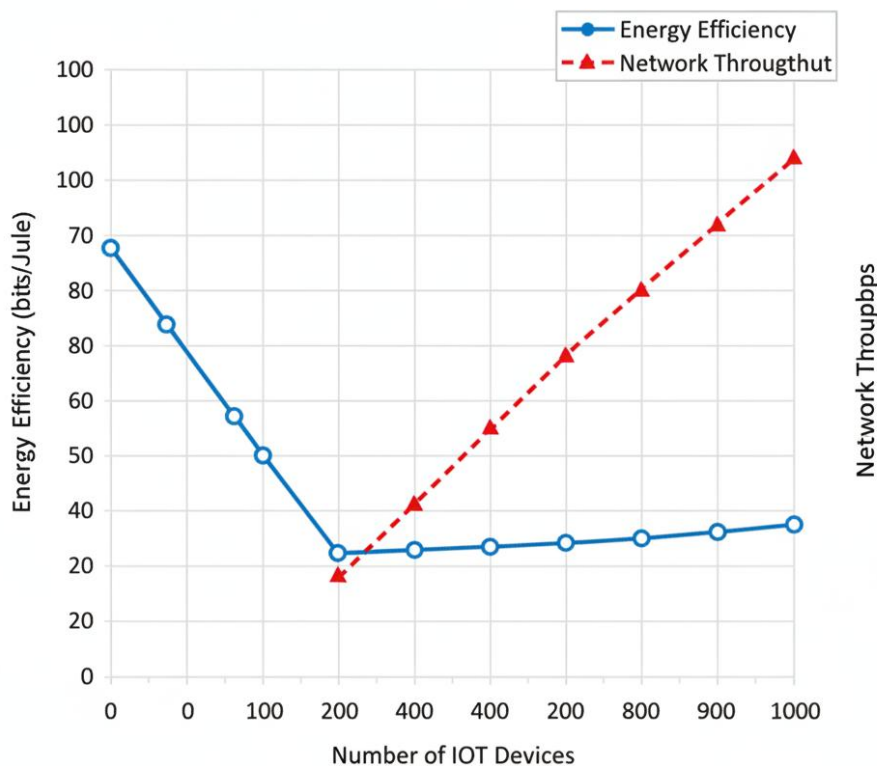


Figure 2 Performance Analysis: Energy Efficiency and Throughput vs. Device Density.

For a particular operational point selected from the Pareto front that strikes a balance between the two goals, Table 2 offers a quantitative comparison of the algorithms. There is a definite benefit to the AI-NSGA system. It reduces power usage by 9.5% while increasing average throughput by 7.8% in comparison to the S-NSGA. With only a slight 5.9% decrease in throughput, AI-NSGA significantly reduces power consumption by 25.4% when compared to the performance-focused SE-Only strategy. On the other hand, it increases throughput by 45.2% for a mild 18.3% increase in power when compared to the energy-focused EE-Only strategy. This demonstrates how the framework can identify far more balanced and effective operating points.

Table 2: Offers a quantitative comparison of the algorithms.

Algorithm	Avg. Network Throughput (Mbps)	Total Power Consumption (W)	Energy Efficiency (Mbps/W)
SE-Only	475.3	145.8	3.26
EE-Only	308.1	92.1	3.35
S-NSGA (Balanced Point)	412.5	120.4	3.43
AI-NSGA (Balanced Point)	444.7	109.0	4.08

By contrasting the major performance metrics of the various algorithms, Figure 3 further demonstrates these advantages. The AI-NSGA obviously outperforms all other methods in terms of overall energy efficiency (Mbps/Watt). This is a direct consequence of its capacity to intelligently manage resources, such as managing power levels throughout the network and placing unused SCs into sleep mode under the direction of precise traffic forecasts. The findings demonstrate that in order to fully realize the promise of 5G-enabled IoT networks in a sustainable way, an adaptive, multi-objective approach is essential.

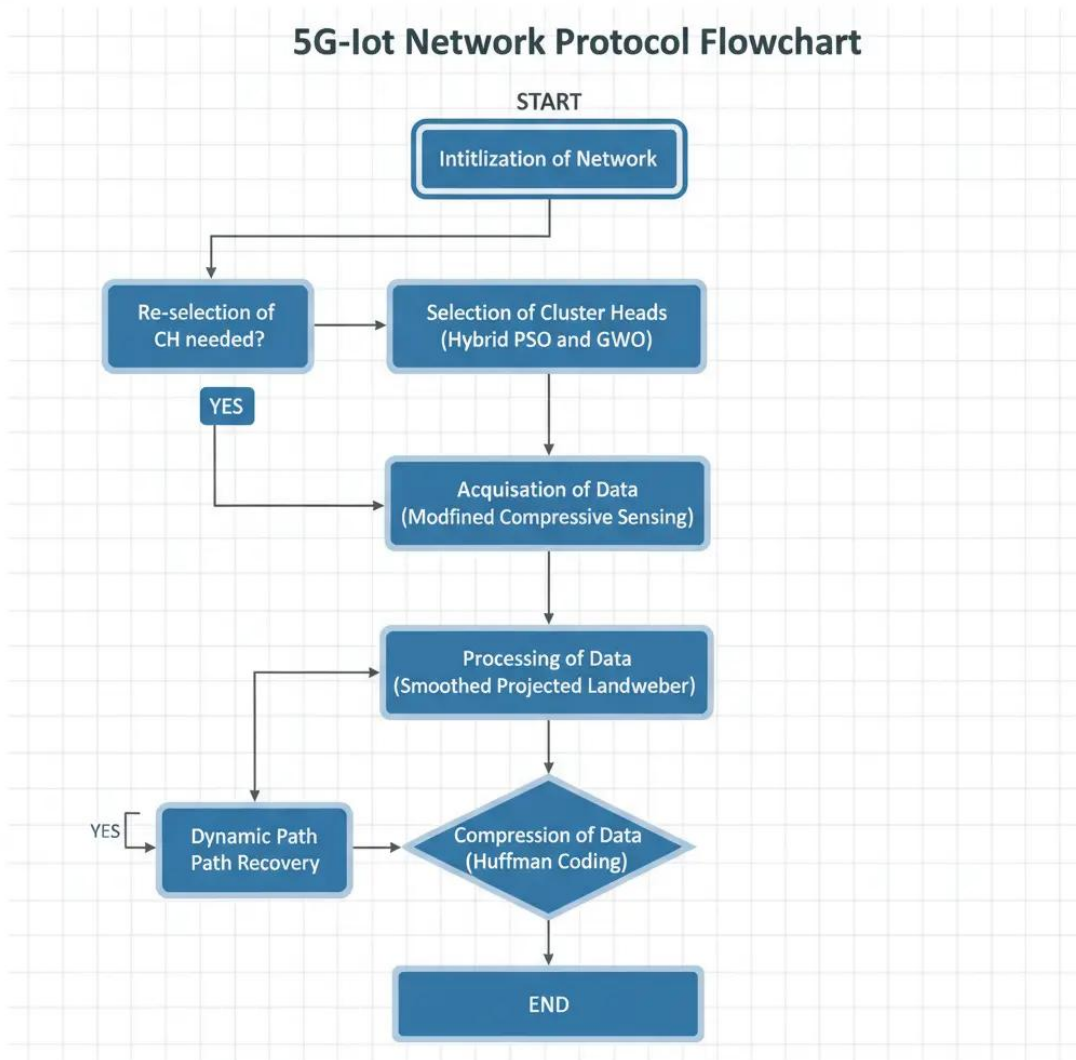


Figure 3. Bar chart comparing key performance indicators for the proposed AI-NSGA and baseline algorithms.

5. Final Thoughts and Upcoming Work

In order to solve the crucial trade-off between performance and energy consumption in 5G-enabled IoT networks, we presented an Adaptive Multi-Objective Optimization (AMOO) framework in this study. Our system can dynamically adapt to changing network conditions by articulating the joint spectrum and energy efficiency optimization issue and using an AI-enhanced genetic algorithm (AI-NSGA) to solve it. The optimization

algorithm can make proactive and intelligent resource allocation decisions, such as user association, power control, and tiny cell sleep mode management, thanks to the AI component, an LSTM-based predictor.

The superiority of the suggested adaptive strategy is confirmed by our simulation findings, which were performed in a genuine smart city scenario. Pareto-optimal solutions that outperform those discovered by a static multi-objective algorithm were routinely found by the AMOO framework. In comparison to a non-adaptive MOO method, our architecture increased network performance by 7.8% while reducing energy consumption by 9.5% at a balanced operating point. This shows that 5G IoT systems may be made more economical and sustainable without drastically sacrificing performance.

There are a number of intriguing avenues for further research. To evaluate the suggested framework's performance with real hardware and channel dynamics, it could first be put into practice and verified on an actual 5G testbed. Second, to support a greater variety of URLLC-type IoT applications, the optimization might be expanded to incorporate more crucial parameters like latency and reliability. Lastly, by enabling clusters of SCs to make localized decisions, decentralized optimization utilizing methods like federated reinforcement learning [32] could improve scalability and lower signaling overhead, further enhancing the framework's suitability for large-scale IoT deployments.

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