Joint SoC-Aware Resource Allocation and Power Control for Future Cellular IoT Networks.

Abstract

Ultra-dense cellular IoT networks are reaching a breaking point where spectrum scarcity, severe co-channel interference, and battery limitations can no longer be addressed by conventional fixed-power resource allocation strategies. This paper tackles this challenge by proposing a State of Charge (SoC)-aware heuristic resource allocation and power control framework for IoT communications underpinning a cellular network. The main objective is to jointly preserve communication performance and battery sustainability in interference-limited environments. To this end, the resource allocation problem is formulated under Quality of Service (QoS), interference, and power constraints, and a low-complexity heuristic solution is developed. Unlike conventional approaches, the proposed framework explicitly integrates the SoC of IoT devices into the transmission decision process, together with channel conditions and interference levels, thereby enabling adaptive and energy-aware resource assignment. Simulation results show that the proposed scheme consistently improves throughput over the considered benchmark while preserving a high level of fairness and maintaining stable energy-efficiency behavior across different network densities and resource configurations. In addition, the proposed power adaptation mechanism significantly reduces unnecessary transmit power and converts this reduction into a measurable battery lifetime improvement. These findings demonstrate that SoC-aware radio resource management is a practical and effective solution for robust, fair, and energy-sustainable ultra-dense IoT deployments.

Keywords: Resource Allocation; Power Control; 5G-NR; Interference management; Massive IoT

1. Introduction

The evolution toward ultra-dense Beyond-5G (B5G) and 6G networks is expected to support an unprecedented number of interconnected Internet of Things (IoT) devices, generating massive traffic volumes and diverse quality-of-service (QoS) requirements [1, 2].

To accommodate this growth while enhancing spectral efficiency and reducing communication latency, future cellular IoT networks are expected to leverage several key technologies, including semantic communications [3], AI-driven resource optimization [4], integrated sensing and communication [5], and direct device-to-device (D2D) communication [6]. In particular, direct IoT communication through Proximity Services (ProSe) has emerged as an effective complement to conventional cellular transmission, enabling nearby devices to exchange information locally, thereby reducing network congestion, lowering end-to-end latency, and improving spectrum efficiency [7, 8, 9].

However, realizing these benefits in ultra-dense cellular environments remains challenging due to the highly coupled interference generated by spectrum sharing and frequency reuse. Therefore, efficient interference management, radio resource allocation, and power control mechanisms are essential to fully exploit the potential of IoT communications while preserving network performance and service reliability [10, 11]. Therefore, the coexistence between IoT users and conventional cellular user equipment (UE) must be carefully managed through efficient resource allocation mechanisms; otherwise, uncontrolled interference may severely compromise the QoS of cellular users [8].

IoT communication is also considered a key enabling technique for 5G networks due to its potential to enhance energy efficiency (EE) while reducing transmission power consumption without compromising data integrity. By enabling direct communication between proximate devices, IoT transmission can achieve substantial improvements in both spectral efficiency and energy efficiency.

When IoT devices share the licensed cellular spectrum, spectrum reuse intensifies co-channel interference, potentially degrading communication reliability and overall network performance if not properly managed [12]. Consequently, energy-efficient radio resource allocation and power control have become fundamental to future cellular IoT networks, enabling efficient spectrum utilization while reducing energy consumption, extending device lifetime, and improving network reliability and sustainability [13].

Furthermore, energy-aware resource allocation contributes to improved system efficiency and congestion mitigation. This can be achieved by minimizing the amount of resources required to accomplish specific communication tasks, thereby lowering total energy expenditure. Efficient resource distribution also reduces operational costs, as less energy is consumed during network operation [12, 14].

From a long-term perspective, optimizing energy consumption in 5G networks yields substantial economic benefits for network operators. In addition, improved EE extends device battery lifetime, thereby reducing the environmental impact associated with frequent battery replacement [15, 16].

Finally, energy-efficient resource allocation enhances the QoS by ensuring optimal and judicious utilization of available resources. This approach improves user experience and enables broader network coverage without performance degradation. By limiting energy consumption, 5G systems can extend connectivity to underserved and rural areas, fostering more inclusive and sustainable digital access [17].

1.1. Related work

The work in [17] presents an intelligent performance analysis of an energy-efficient resource allocation model (EERAM) for D2D communication in 5G Wireless Personal Area Networks (WPAN). The proposed model aims to optimize resource usage to reduce energy consumption, extend device lifespan, lower communication costs, and minimize environmental impact. Experimental results demonstrate high efficiency across multiple metrics, including 92.97% energy allocation, 88.72% power allocation, and 94.33% network data speed, with a notable reduction in end-to-end delay to 25.47%.

The paper in [18] presents a robust and energy-efficient resource allocation mechanism utilizing a polynomial-time proportional fair (PF) scheduling algorithm. The framework provides minimum rate assurances for cellular users while adaptively distributing multiple resource blocks (RB) to IoT pairs in response to fluctuating channel conditions. A greedy heuristic is utilized to address the mixed-integer nonlinear optimization problem in the context of real-time scheduling.

The study in [19] proposes a novel approach to improve power allocation and throughput in 5G cellular networks by leveraging D2D communication and a modified Gale-Shapley algorithm. The method is evaluated under two scenarios: conventional 5G operations emphasizing energy efficiency and signal reliability, and a disaster scenario where IoT devices autonomously maintain connectivity in the absence of base stations.

The article in [7] addresses key limitations in implementing the Optimized Link State Routing (OLSR) protocol, including poor link quality, high energy consumption, and excessive processor load. It introduces an energy-efficient link sensing and database maintenance strategy, featuring a revised control message sequence and an adaptive multipoint relay (MPR) selection method based on battery level, mobility, node degree, and base station connectivity. Implemented in NS-3, the enhanced OLSR demonstrates superior performance over OLSRv2 and other protocols in terms of energy efficiency, routing overhead, packet delivery ratio, and end-to-end delay.

Later, in [20], we proposed a heuristic algorithm for fair resource allocation in ultra-dense $5G/6G$ networks, where a large number of IoT devices coexist and share the radio spectrum with cellular users. The objective of the proposed scheme is to maximize aggregate throughput while effectively mitigating interference and ensuring compliance with SINR thresholds for both categories of users. Simulation results indicate that the algorithm consistently achieves high data rates, surpassing 30 Gbps, thereby demonstrating a substantial improvement in overall system capacity.

Specifically, throughput values of up to 17 Gbps are observed at -20 dBm, while rates in the range of 29–31 Gbps are achieved at 0 dBm for cellular users. For IoT devices, the total throughput varies between 17 and 29 Gbps depending on transmission power levels and device density.

A notable feature of the proposed algorithm is its scalability: it maintains high throughput even in scenarios involving 700 to 1100 IoT devices, a performance rarely attained by competing approaches. Moreover, the algorithm ensures strong fairness among users, with the Jain Fairness Index (JFI) consistently exceeding

0.95 across all tested scenarios, thus reflecting excellent equity. The Efficiency Ratio (ER) remains within the interval 0.7–0.99, indicating a relatively balanced distribution of radio resources. Importantly, the scheme prevents IoT traffic from overwhelming cellular users, thereby preserving QoS. Its linear computational complexity further supports practical applicability in massive Machine-Type Communication (mMTC) environments. Despite these promising results, the algorithm does not perform joint optimization of transmission power and resource block (RB) allocation. Transmission power remains fixed, which inherently limits energy and spectral efficiency compared to fully optimized models that incorporate power adaptation. Despite these advances, most existing works mainly address generic IoT scenarios and do not sufficiently consider the specific requirements of Industrial Internet of Things (IIoT) networks. This gap is important because IIoT deployments involve massive numbers of sensors, actuators, controllers, and industrial devices operating under strict constraints of reliability, latency, energy autonomy, and interference control. Consequently, recent IIoT-oriented studies must be considered to better position the proposed SoC-aware resource allocation framework within the context of green, reliable, and energy-sustainable industrial wireless networks.

Recent studies have emphasized that Industrial Internet of Things (IIoT) networks represent one of the most demanding application domains for beyond-5G and 6G wireless systems. In IIoT environments, a massive number of sensors, actuators, robots, controllers, and monitoring devices must exchange information with stringent requirements in terms of reliability, latency, energy efficiency, and service continuity. The work in [21] showed that energy-efficient IIoT in green 6G networks requires the joint integration of distributed artificial intelligence, edge/cloud computing, intelligent decision algorithms, and sustainable resource management. Their study highlights that energy-aware communication and green computing techniques are essential for smart industrial equipment, manufacturing environments, and cyber-physical production systems. More specifically, concrete resource allocation problem in relay-assisted NOMA-WPT Industrial IoT networks was addressed in [22], where the objective is to minimize communication delay while jointly considering wireless power transfer, relay cooperation, and NOMA-based access. Their work shows that IIoT resource management is not limited to generic throughput maximization, but must also account for latency, energy availability, and service reliability in industrial scenarios. This observation is closely aligned with the motivation of the present work, where the proposed SoC-aware resource allocation and power control framework aims to improve throughput and fairness while reducing unnecessary transmit power and extending the lifetime of battery-constrained IoT/IIoT devices.

1.2. Motivation, Main idea and Contribution

Although the previous study [20] demonstrates high performance in terms of throughput and fairness within an ultra-dense IoT environment, it exhibits a significant limitation regarding the consideration of energy efficiency. Specifically, power management is treated in a static manner: IoT devices transmit using a predefined power level, and the algorithm merely verifies whether the Signal-to-Interference-plus-Noise Ratio (SINR) thresholds are satisfied. No dynamic power adaptation is performed based on channel conditions, network density, or the energy status of the devices.

Moreover, although energy efficiency is mentioned in the performance evaluation, no explicit modeling of energy consumption, battery lifetime, or SoC is incorporated into the system model.

This limitation is particularly critical in mMTC scenarios, where IoT devices are typically battery-powered and expected to operate for extended periods without maintenance. In such contexts, merely maximizing throughput or satisfying SINR constraints is insufficient; intelligent power control becomes a decisive factor in ensuring network sustainability and communication reliability.

Therefore, it is necessary to design an energy-aware power control algorithm capable of dynamically adjusting transmission power not only according to interference and QoS constraints but also based on energy-related parameters such as SoC and the distance between communicating devices. Such an approach would reduce overall energy consumption, balance resource utilization between devices with low and high energy levels, and significantly extend the operational lifetime of ultra-dense IoT networks.

By explicitly integrating energy efficiency into the decision-making process, the proposed algorithm would overcome the limitations of the previous model and provide a more realistic and sustainable solution aligned with the requirements of future 5G/6G IoT-oriented networks. Therefore, beyond conventional IoT/D2D scenarios, the proposed SoC-aware allocation framework is also relevant for IIoT networks, where battery-constrained devices, dense deployments, interference-limited communications, and long-term autonomous operation are critical requirements.

2. System Model and Problem Formulation

2.1. System Description

Let's consider a 5G-NR with a single cell centered on the gNB (next-generation NodeB) base station, as described in Fig. 1. IoT users randomly access resources allocated to cellular users, improving spectral efficiency, while cellular users are assigned dedicated RBs. IoT transmitters reuse these RBs for direct communication, introducing interference. We therefore consider two communication types within the cell. We denote by 1) $\mathcal{U}$ the set of conventional cellular UEs, $\mathcal{U} = \{1,2,\cdots,N_c\}$, of size N_c, and 2) $\mathcal{D}$ the set of IoT devices, $\mathcal{D} = \{1,2,\cdots,N_d\}$, of size N_d. Table 1 lists the symbols and notations used in this work:

Table 1. Symbols and notations.

Notation	Description
$\mathcal{U}$	The set of UEs
$\mathcal{D}$	The set of IoT devices
$\mathcal{R}$	The set of RBs
N_c	The number of UEs
N_d	The number of IoT devices
$N_d^{'}$	The effective number of IoT devices reusing the same resource as the cellular UE
$h_{c,d_{TX}}$	The channel gain between a UE and an IoT device
$h_{d'_{TX},d_{RX}}$	The link gain between two IoT devices
P_d	The power emitted by the IoT transmitter
$P_d^{'}$	The power emitted by other IoT devices
P_c	The power emitted by the UE
ω_c	The white Gaussian noise at the UE
ω_d	The white Gaussian noise at the IoT receiver
γ_d	The IoT device SINR
γ_d^{thr}	The IoT device SINR threshold
γ_c	The UE SINR
γ_c^{thr}	The UE SINR threshold

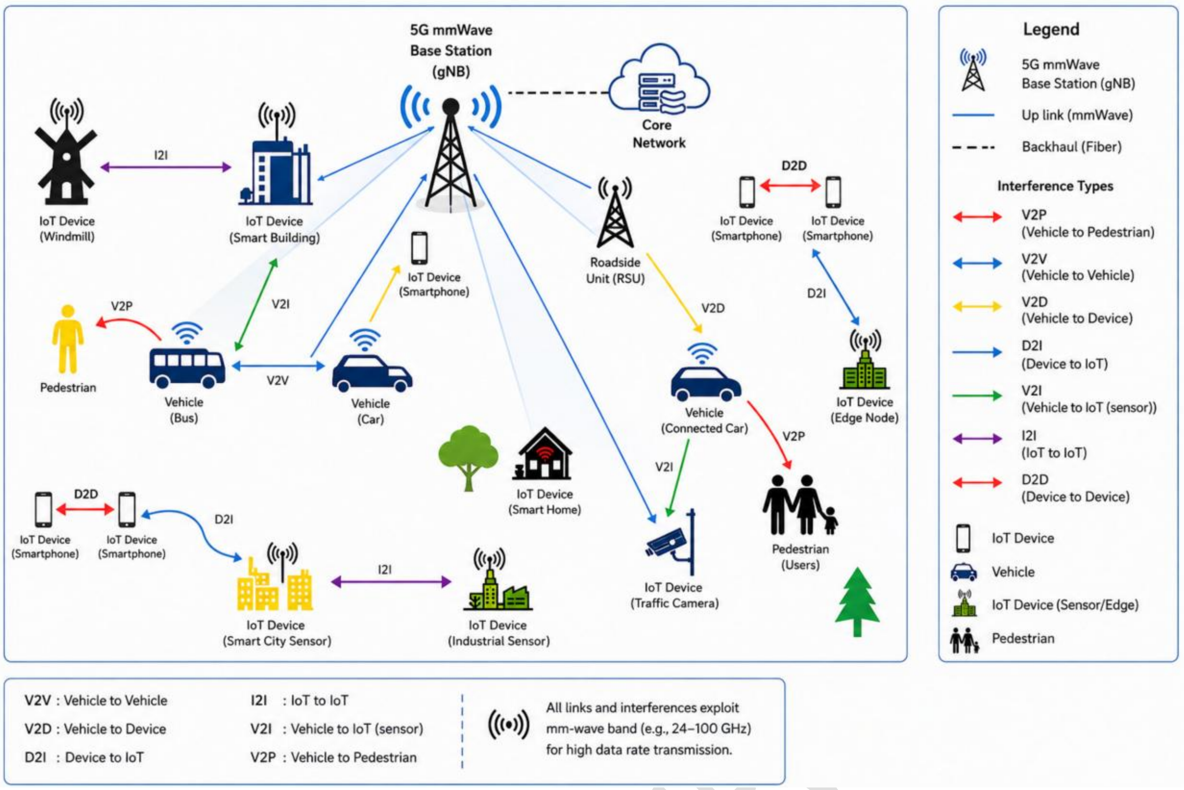

Figure 1. An ultra-dense 5G IoT environment architecture.

In the considered system model, the resource grid is represented as a matrix $\mathcal{R}(N_f, N_t)$, where N_f denotes the number of subcarriers and N_t the number of time symbols [23]. $\mathcal{R}$ the set of RBs $N_{RB} = N_t \times N_f$ of size N_{RB}, it's a $\mathcal{R}(N_f, N_t)$ matrix that has N_f rows corresponding to the frequency subdivision and N_t columns representing the number of time slots. The number of block resources is therefore $N_{RB} = N_f \times N_t$.

Conventional cellular users are assigned dedicated RBs, while IoT devices opportunistically reuse these resources for direct communication. Although this reuse enhances spectral efficiency, it may introduce interference when multiple users access the same RB. Therefore, both interference-free and interference-limited scenarios must be considered, depending on the resource sharing conditions [20].

To ensure QoS, IoT users must satisfy a minimum SINR (signal-to-interference-plus-noise ratio) threshold. Interference may arise from various sources (e.g., V2V, V2D, D2I, I2I, V2I, V2P) operating in the mmWave band across diverse environments. This interference can degrade UE performance, particularly data rates [20]. Therefore, an optimization model is proposed to mitigate its impact on conventional communications based on the SoC battery of IoT.

2.2. Problem Formulation

IoT users opportunistically reuse the RB assigned to cellular users for direct communication. Each cellular user is allocated one RB, and the total number of RBs, N_{RB} is equal to N_c. When multiple IoT users reuse the same RB, interference is introduced at both cellular and IoT receivers.

To this interference, the white Gaussian noise ω_c is added. Consequently, the SINR at the UE, which we denote as γ_c, is given by the following formula:

$$\gamma_c = \frac{P_c h_{c,d}}{\sum_{d=1}^{N_d'} P_d h_{c,d_{TX}} + \omega_c} \tag{1}$$

where P_d is the power emitted by the IoT link transmitter, P_c is the power of the UE transmitter, N_d' is the effective number of IoT users reusing the same resource as the cellular UE, and $h_{c,d_{TX}}$ is the channel gain between a UE and an IoT user. To ensure a certain QoS, that is, the throughput of the UE, γ_c must be greater than the threshold γ_c^{thr}: $\gamma_c \geq \gamma_c^{\mathrm{thr}}$ to ensure that the cellular UE communicates with the required performance. Similarly, we define for the IoT the SINR given by:

$$\gamma_d = \frac{P_{d_{TX}} h_{d_{TX},d_{RX}}}{P_c h_{c,d_{RX}} + \sum_{d'=1,d'\neq d}^{N_d} P_{d'_{TX}} h_{d'_{TX},d_{RX}} + \omega_d} \geq \gamma_d^{\mathrm{thr}}. \tag{2}$$

where $P_d^{'}$ is the power emitted by the transmitter of the other IoT user links, $h_{c,d_{RX}}$ and $h_{d'_{TX},d_{RX}}$ respectively, refer to the channel gain between the IoT transmitter and the UE, as well as the link gain between the IoT and all IoT users, where γ_d^{thr} is the SINR threshold at which IoT users communicate.

The SINR expressions for cellular and IoT users remain as defined in equations (1) and (2). However, unlike conventional approaches, the transmission power of IoT devices is no longer considered static. Instead, it is dynamically adapted based on the SoC of each IoT device.

Let $SoC_d \in [0,1]$ denote the normalized battery level of the IoT device. To incorporate energy-awareness, we define a SoC-dependent power control policy such that: 1) Devices with low SoC reduce their transmission power to conserve energy, and 2) Devices with high SoC are allowed to transmit with higher power. The power of transmission of IoT will be according to the SoC defined as follows: $P_d = f(d, SoC_d, \alpha)$ where d is the distance between the transmitter and receiver of IoT communication, SoC_d is the battery state of IoT, and α is a coefficient of ponderation for the increase of P_d increasing. The SoC_d must be greater than a threshold value: $SoC_d \geq SoC_d^{\mathrm{thr}}$ to ensure the communication.

The SINR is adopted as a fundamental metric to evaluate link quality for both cellular and IoT users. Based on the Shannon–Hartley theorem, the achievable data rates for IoT and UE are directly determined by the SINR. Specifically, the throughput of cellular and IoT links can be expressed as:

$$R_c = B\log_2(1+\gamma_c), \tag{3}$$

and

$$R_d = B\log_2(1+\gamma_d). \tag{4}$$

The total data throughputs of traditional communications and IoT links are then:

$$R_{TOTc} = \sum_{c=1}^{N_c} R_c = \sum_{c=1}^{N_c} B\log_2(1+\gamma_c), \tag{5}$$

and

$$R_{TOTd} = \sum_{d=1}^{N_d} R_d = \sum_{d=1}^{N_d} B\log_2(1+\gamma_d). \tag{6}$$

where B denotes the system bandwidth, while γ_c and γ_d represent the SINR of cellular and IoT users, respectively. These expressions characterize the maximum achievable data rates under given channel conditions and interference levels. Consequently, they provide the theoretical foundation for evaluating system performance and formulating the resource allocation optimization problem.

So, the objective of this work is to develop an efficient and energy-aware resource allocation framework that jointly maximizes the aggregate throughput of cellular and IoT users while satisfying stringent QoS requirements. Beyond throughput maximization, the proposed formulation explicitly enforces a balanced performance between cellular and IoT users, ensuring that neither class of users experiences significant degradation due to spectrum reuse. The problem is formulated as the following constrained optimization program:

$$\begin{aligned} &(P1)\text{: Maximize} \quad \left(\sum_{c=1}^{N_c} R_c + \sum_{d=1}^{N_d} R_d \right) \\ &\text{Subject to: C1:} \quad \gamma_c \geq \gamma_c^{\mathrm{thr}} \\ &\text{C2:} \quad \gamma_d \geq \gamma_d^{\mathrm{thr}} \\ &\text{C3:} \quad P_c \leq P_c^{\max} \\ &\text{C4:} \quad P_d \leq P_d^{\max} \\ &\text{C5:} \quad SoC_d \geq SoC_d^{\mathrm{thr}} \end{aligned} \tag{7}$$

Constraints C_1 and C_2 ensure the minimum SINR requirements for reliable communication, whereas C_3 and C_4 bound the transmission power of cellular and IoT devices. Importantly, constraint C_5 introduces an energy-awareness dimension by incorporating the battery state (SoC) of IoT devices, thereby promoting sustainable operation and prolonging network lifetime. The resulting problem belongs to the class of mixed-integer non-linear programming (MINLP) problems and is inherently NP-hard due to the combinatorial nature of resource allocation and the non-linear coupling between interference, power control, and channel conditions. Consequently, obtaining a globally optimal solution is computationally intractable for large-scale ultra-dense networks. To address this limitation, a scalable and low-complexity heuristic algorithm is proposed in the following section, capable of achieving near-optimal performance while accounting for the large number of IoT and cellular users.

3. Proposed Algorithm

In this section, we describe a proposed heuristic algorithm in detail. Its pseudocode is presented in flowchart form in Fig. 2.

3.1. Algorithm Description

The proposed SoC-aware heuristic algorithm described in Fig. 2 operates over the set of IoT users $\mathcal{D}$ in a single-cell 5G-NR environment, where the set of available RBs is denoted by $\mathcal{R}$. We assume that each cellular user is initially assigned one dedicated resource block, so that the IoT devices opportunistically reuse the already occupied RBs in underlay mode. The objective of the algorithm is to perform energy-aware resource assignment while satisfying the QoS constraints defined in the optimization problem.

For each IoT user $d \in \mathcal{D}$, the algorithm starts with a SoC-based admission control. Let $\mathrm{SoC}_d^{\mathrm{thr}}$ be the minimum admissible threshold. The device is considered eligible only if

$$\mathrm{SoC}_d > \mathrm{SoC}_d^{\mathrm{thr}}. \tag{8}$$

If this condition is not satisfied, the user is rejected from the current allocation attempt. This preliminary filtering stage avoids assigning radio resources to devices with critically low residual energy.

For each eligible IoT device, one resource block $r_d \in \mathcal{R}$ is randomly selected. The propagation conditions of the corresponding IoT link are then characterized through path-loss estimation. Let d denote the distance between the transmitter and the receiver of the considered IoT pair, and let $PL(d)$ denote the associated path loss. Based on the target SNR requirement, the minimum transmit power required for communication is computed as

$$P_{tx,d}^{\min} = \frac{\mathrm{SNR}_{\mathrm{thr}}\, N_0\, PL(d)}{G_{tx} G_{rx}}, \tag{9}$$

where N_0 is the noise power, and G_{tx} and G_{rx} denote the transmitter and receiver antenna gains, respectively. This quantity provides the minimum power level required to compensate for propagation attenuation while meeting the desired link-quality target.

Using this initial power level, the first SINR evaluation is carried out. The IoT SINR on the selected RB is given by

$$\gamma_d = \frac{P_{tx,d}^{\min} h_{dTX,dRX}}{P_c h_{c,dRX} + \sum_{d'=1 d' \neq d}^{N_d{}'} P_{d'TX}\, h_{d'TX,dRX} + \omega_d}, \tag{10}$$

where $h_{dTX,dRX}$ denotes the channel gain of the intended sidelink, $h_{c,dRX}$ is the channel gain between the cellular transmitter and the IoT receiver, $h_{d'TX,dRX}$ is the interference channel gain from co-channel IoT transmitters, and ω_d is the additive noise term. The first decision stage verifies whether the selected RB can be used directly without any SoC-based correction, that is,

$$\gamma_d \geq \gamma_d^{\text{thr}} \quad \text{and} \quad P_{tx,d}^{\min} \leq P_d^{\max}. \tag{11}$$

If the above condition is satisfied, the selected RB is allocated without SoC weighting. In this case, the device transmits with the minimum required power, which avoids unnecessary energy expenditure while preserving the QoS requirement. The allocation indicator associated with user d and resource r_d can then be set to

$$x_{d,r_d} = 1. \tag{12}$$

After this allocation, the system state is updated to reflect both the new RB occupancy and the modified interference pattern.

If the initial SINR and power constraints are not satisfied, the algorithm activates the SoC-aware power adaptation stage. A weighting factor α_d is first computed as

$$\alpha_d = 1 + \frac{\text{SoC}_d}{\text{SoC}_d^{\text{thr}}}. \tag{13}$$

This coefficient increases with the battery level of the device, meaning that users with higher residual energy are allowed to sustain a more aggressive transmit-power adaptation, while users with low energy remain more conservative. Based on this factor, an intermediate weighted power is defined as

$$P_{\text{est},d} = \alpha_d P_{tx,d}^{\min}. \tag{14}$$

The actual transmit power is then bounded by the maximum admissible power as

$$P_{tx,d} = \min\left(P_d^{\max}, P_{\text{est},d}\right). \tag{15}$$

Using this updated power level, the SINR is re-evaluated as

$$\gamma_d^{(\text{new})} = \frac{P_{tx,d} h_{dTX,dRX}}{P_c h_{c,dRX} + \sum_{d'=1 d' \neq d}^{N_d{}'} P_{d'TX}\, h_{d'TX,dRX} + \omega_d}. \tag{16}$$

The second decision stage verifies whether the weighted power is sufficient to satisfy the communication requirements:

$$\gamma_d^{(\text{new})} \geq \gamma_d^{\text{thr}} \quad \text{and} \quad P_{tx,d} \leq P_d^{\max}. \tag{17}$$

If this condition is satisfied, the selected RB is allocated to user d, namely:

$$x_{d,r_d} = 1. \tag{18}$$

Otherwise, the allocation attempt is rejected, and the device is not admitted to the selected resource during the current iteration.

Whenever an allocation is successful, the throughput of the corresponding sidelink is updated according to the Shannon–Hartley expression as stated in equation (4), or, after weighting,

$$R_d = B \log_2\left(1 + \gamma_d^{(\text{new})}\right), \tag{19}$$

depending on the branch followed by the device. Consequently, the aggregate IoT throughput is updated as

$$R_d^{\mathrm{TOT}} = \sum_{d=1}^{N_d} R_d. \tag{20}$$

Overall, the proposed solution combines three key mechanisms: SoC-based admission control, interference-aware SINR verification, and SoC-dependent transmit-power adaptation. This structure enables the algorithm to preserve QoS feasibility, improve energy sustainability, and reduce unnecessary transmission power while maintaining a scalable allocation strategy for ultra-dense 5G-NR IoT environments.

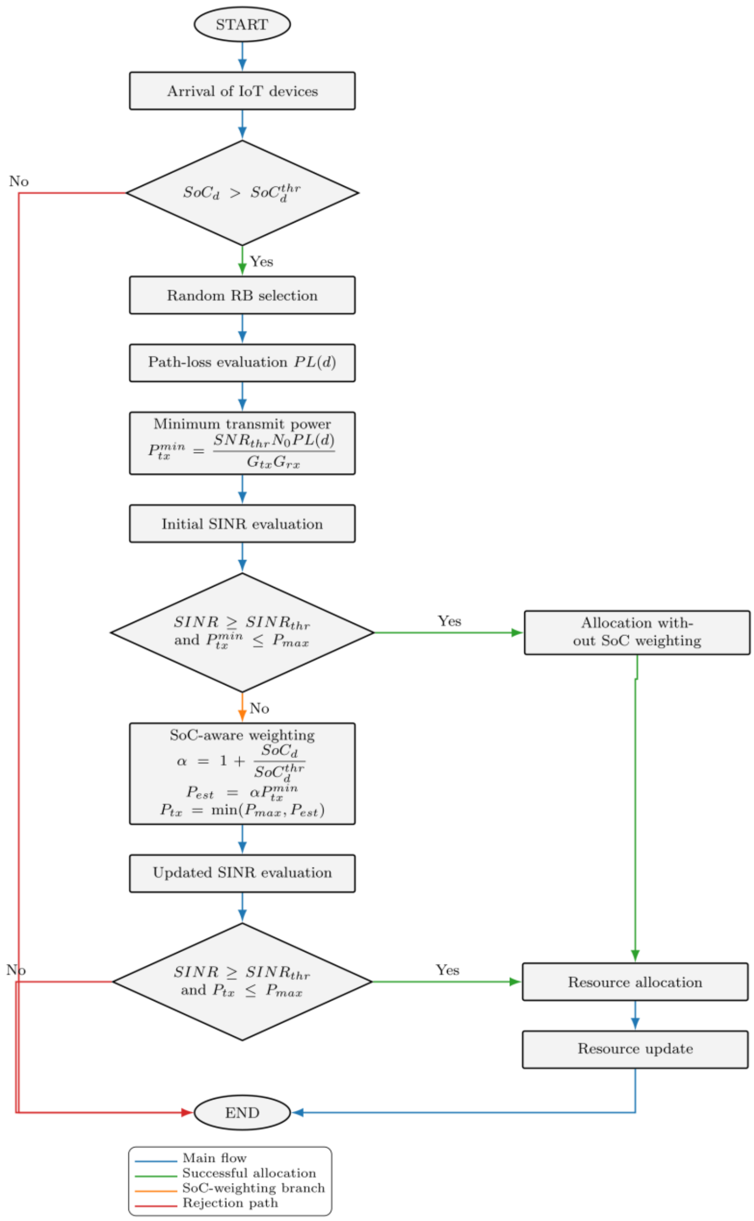

Figure 2. Proposed SoC-aware heuristic resource allocation algorithm for IoT.

3.2. Computational Complexity Analysis

The temporal complexity of the updated SoC-aware heuristic is mainly dominated by the SINR evaluation stage, whereas SoC checking, random RB selection, path-loss estimation, minimum transmit power computation, and SoC-based weighting all require constant time. Let K_d denote the average number of co-channel interferers experienced by IoT user d. Since the first SINR computation involves summing the interference contribution of these users, its complexity is $O(K_d)$. In the weighted branch, an additional SINR re-evaluation is performed after SoC-based power adaptation, which also requires $O(K_d)$ operations.

Therefore, the per-user complexity remains $O(K_d)$, although with a slightly higher constant factor than in the previous version. For N_d IoT users, the total temporal complexity is thus $O(N_d K_d)$. Assuming a uniform reuse of the available N_{RB} RBs, one IoT user has

$$K_d \approx \frac{N_d}{N_{RB}},$$

which leads to the average-case complexity

$$O\left(\frac{N_d^2}{N_{RB}}\right).$$

In the worst-case scenario, where many users reuse the same RB, the complexity increases to $O\left(N_d^2\right)$. Therefore, the updated scheme preserves low computational complexity and remains scalable for ultra-dense 5G-NR IoT deployments while providing a more realistic SoC-aware decision process and improved energy sustainability.

4. Simulation and Results Analysis

This section evaluates the performance of the proposed SoC-aware resource allocation algorithm through extensive simulations. The considered scenario corresponds to a single-cell 5G-NR system with underlay IoT communication, where IoT devices opportunistically reuse the RBs assigned to cellular users. The simulations are conducted under varying network densities, with $N_d = 300,700,1100$ IoT devices, in order to assess the scalability of the proposed approach. The number of RBs N_{RB} is varied to analyze its impact on system performance. Table 2 lists the values of the simulation parameters.

Fig. 3 illustrates the average throughput achieved by IoT users as a function of the number of RBs, both before and after optimization. The results clearly show that the proposed SoC-aware scheme consistently outperforms the [20] approach across all considered scenarios. A noticeable throughput gain is observed for all values of N_d, confirming the effectiveness of the proposed optimization strategy. From a system-level perspective, the throughput initially increases with the number of RBs. This behavior is expected, as additional resources reduce contention and improve access opportunities for IoT devices.

Table 2. Simulation parameters.

Parameter	Value
Cell radius	500 m
Frequency	38 GHz
Uplink subcarrier bandwidth	120 kHz
Number of IoT devices	50 to 2000
Number of cellular UEs	50 to 2000
Maximum power of UE-Tx	-20 to 40 dBm
Maximum power of IoT user-Tx	-20 to 40 dBm
IoT pair distance	5 to 200 m
Thermal noise power density for cellular UE	-174 dBm/Hz
Thermal noise power density for IoT user	-134 dBm/Hz
Path loss model of cellular	$128.1 + 37\log\left(d\ (\mathrm{km})\right)$
Path loss model of D2D	$148.1 + 40\log\left(d\ (\mathrm{km})\right)$

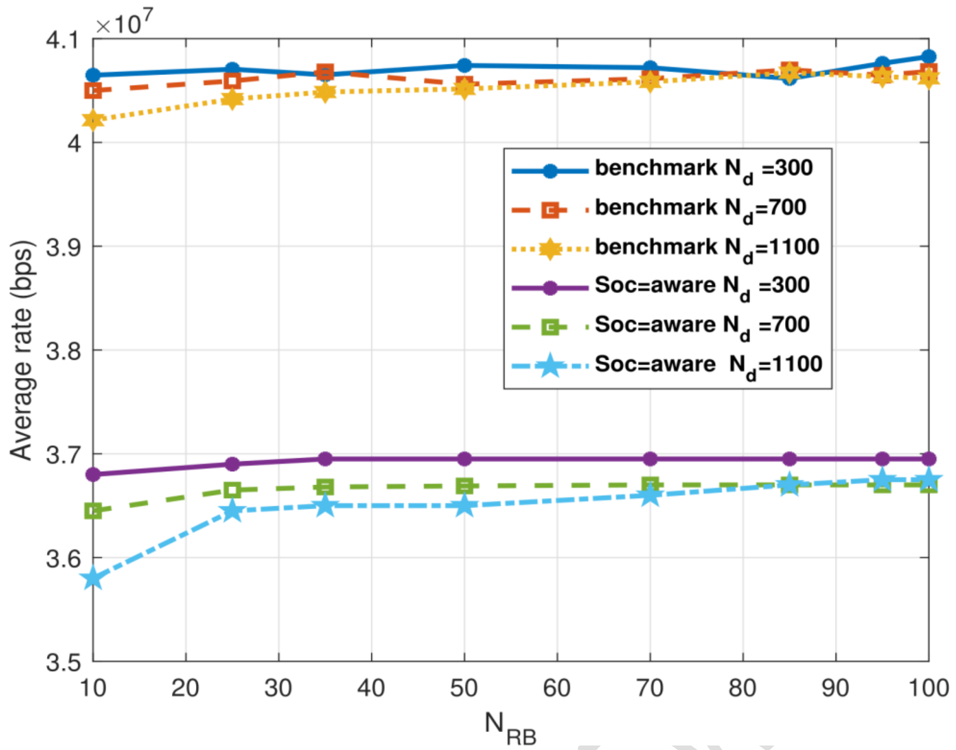

Figure 3. Average rate of IoT users as a function of the number of resources.

4.1. Quantitative Performance Comparison and Scalability

To further quantify the performance improvement, we evaluate the relative throughput gain achieved by the proposed SoC-aware scheme compared to the considered approach (without optimization). The percentage gain is computed as

$$\text{Gain}(\%) = \frac{R_{\text{proposed}} - R_{\text{baseline}}}{R_{\text{baseline}}} \times 100 \tag{21}$$

where R_{proposed} denotes the IoT throughput achieved by the proposed scheme and R_{baseline} corresponds to the throughput obtained in [20]. The resulting values for different IoT densities are summarized in Table 3.

Table 3. Relative Throughput Gain for Different Values of N_d.

N_d	**Benchmark**	**Proposed**	**Gain (%)**
300	3.69×10^7	4.08×10^7	10.6
700	3.67×10^7	4.07×10^7	10.9
1100	3.66×10^7	4.06×10^7	10.9

A quantitative comparison between the proposed SoC-aware scheme and the baseline approach shows that the proposed method achieves a consistent throughput improvement of approximately 10–11% across all network densities, as reported in Table 3. This gain remains remarkably stable as the number of IoT devices increases, demonstrating the robustness and scalability of the proposed algorithm.

To complement the throughput analysis, the fairness of the achieved resource allocation is evaluated through the Jain fairness index, defined as

$$JFI = \frac{\left(\sum_{d=1}^{N_d} R_d\right)^2}{N_d \sum_{d=1}^{N_d} R_d^2}. \tag{22}$$

As shown in Fig. 4, the Jain fairness index (JFI) remains consistently high, with values close to 0.95 for all considered values of N_{RB} and N_d.

Even in the most constrained case, the fairness remains above approximately 0.94, which indicates that the throughput enhancement achieved by the proposed scheme does not come at the expense of allocation equity among IoT users. On the contrary, the proposed algorithm ensures a balanced distribution of radio resources while preserving a high aggregate throughput.

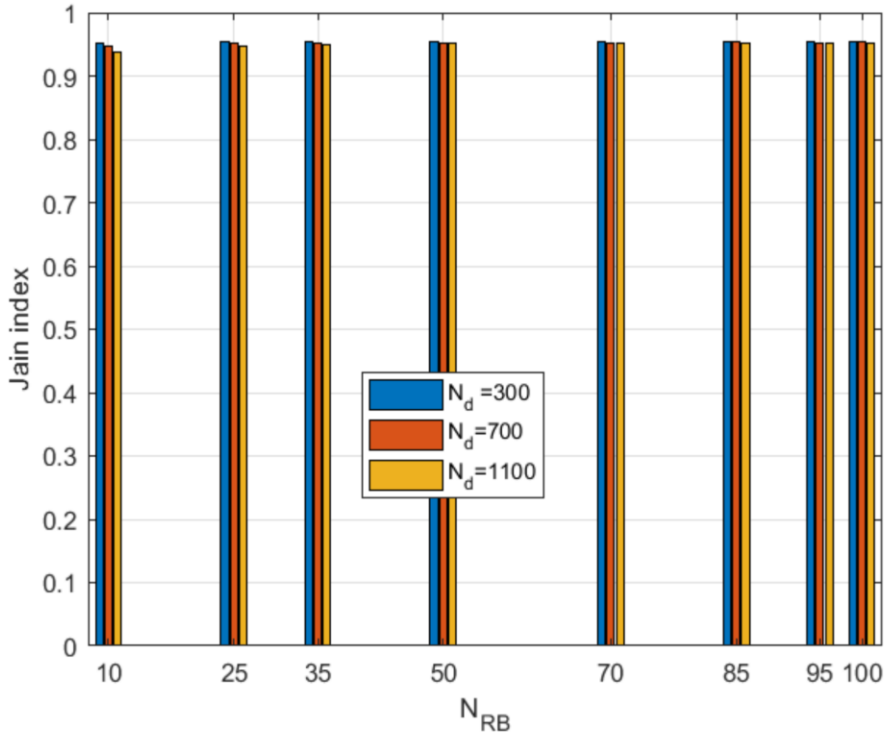

Figure 4. Jain fairness index of IoT users.

The impact of IoT device density is further analyzed to assess the scalability of the proposed framework. As shown in Fig. 3, the proposed algorithm maintains stable throughput performance even for large values of N_d, demonstrating strong robustness in ultra-dense scenarios. This behavior is mainly driven by the explicit integration of the SoC into the resource allocation process. By jointly considering channel conditions, interference levels, and device energy states, the proposed scheme enables adaptive and energy-aware transmission decisions. In particular, the SoC-aware mechanism limits inefficient transmissions from low-energy devices, thereby reducing interference and stabilizing system performance.

As the number of IoT devices increases, the throughput remains nearly unchanged, while the fairness index also remains almost constant. This joint stability in terms of both throughput and fairness confirms the scalability of the proposed approach. Overall, the incorporation of SoC ensures not only performance stability and energy sustainability but also equitable resource sharing, making the proposed method particularly well suited for large-scale and ultra-dense IoT networks.

4.2. Power Optimization and Battery Lifetime

Figure 5 illustrates the average transmit power of IoT devices as a function of the number of RBs N_{RB} for different network densities, for both the approach in [20] and the proposed optimization scheme.

In [20], the transmit power is fixed at 23 dBm regardless of the number of RBs or network conditions. As a result, the corresponding curves remain constant across all values of N_{RB}, reflecting the absence of any adaptive power control mechanism. In contrast, the proposed SoC-aware scheme exhibits a clear reduction in IoT transmission power, which drops from 23 dBm to 7.7 dBm, varying with N_{RB}. This behavior indicates that the algorithm dynamically adjusts the transmission power according to both channel conditions and device energy states.

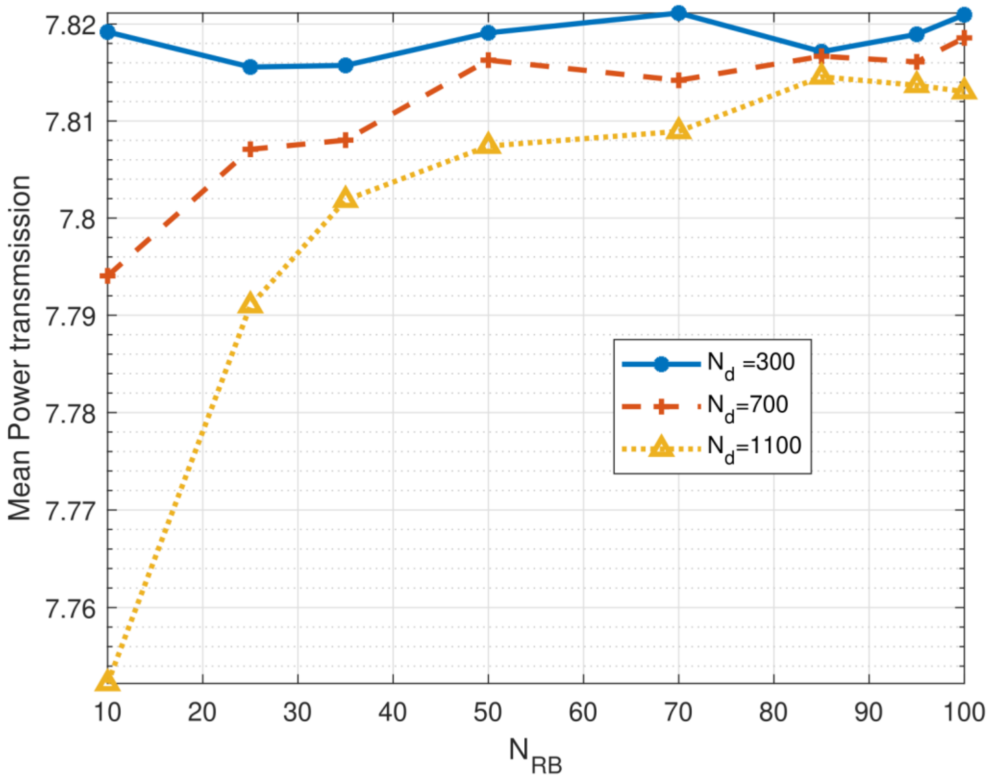

Figure 5. Mean IoT transmit power.

Within this framework, the power reduction achieved by the proposed method is further translated into battery lifetime extension, providing a practical and application-oriented assessment of its impact. To ensure a realistic evaluation of energy efficiency, a device-level energy consumption model is adopted, where the total power is expressed as the sum of a base component and a transmission-dependent component, rather than relying on simplified RF-only assumptions [24, 25, 26, 27, 28].

Specifically, the total power is modeled as

$$P_{\text{total}} = P_{\text{base}} + DC \times \eta \times P_d, \tag{23}$$

where P_{base} accounts for system-level consumption, DC denotes the duty cycle, which is a measure of the fraction of time during which a mobile phone is transmitting [28], and η captures power amplifier inefficiency. This model provides a more accurate estimation of battery lifetime in practical smartphone-based IoT scenarios [24].

The battery lifetime can be estimated from the ratio between the available battery energy and the average total power consumed by the device. Let E_{bat} denote the total energy stored in the battery, expressed in joules (J) or watt-hours (Wh). This quantity represents the maximum amount of electrical energy that can be delivered by the battery during device operation. Given the device-level total power consumption P_{total}, the time required to deplete the battery is expressed as:

$$T = \frac{E_{\text{bat}}}{P_{\text{total}}} = \frac{\mathrm{E}_{bat}}{P_{\text{base}} + DC \times \eta \times P_d} \tag{24}$$

The difference ΔT between the discharge time of the battery obtained after applying our optimization method and the discharge time without optimization quantifies the extension of battery lifetime as:

$$\Delta T = E_{\text{bat}} \left(\frac{1}{P_{\text{base}} + DC\,\eta\,P_d} - \frac{1}{P_{\text{base}} + DC\,\eta\,P_{tx}} \right) \tag{25}$$

In the context of 5G-NR, representative parameter values are provided in Table 4.

Table 4. Typical 5G-NR values for the device-level energy model.

Param.	Meaning	Typical 5G-NR value
P_{TX}	IoT transmit power	23 dBm (200 mW) [29]
DC	Duty cycle	0.05–0.20; nominal value: 0.10 [28]
P_{base}	Base device power	≈ 0.59 W [27]
P_{total}	Total device power	≈ 0.59–1.10 W [27]
η	PA inefficiency factor	2.9–3.2; nominal value: 3 [30]

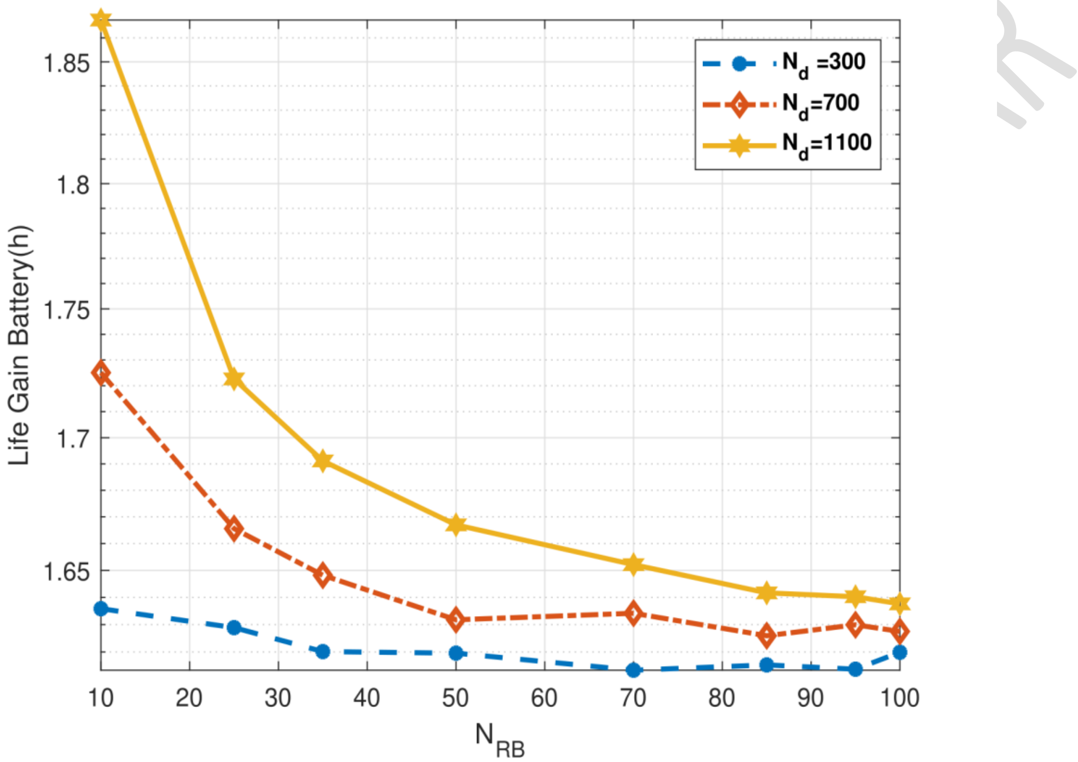

Figure 6. Battery lifetime gain.

Fig. 6 illustrates the battery lifetime gain achieved by the proposed SoC-aware scheme as a function of N_{RB} for different IoT densities. The results indicate a consistently positive lifetime improvement, exceeding approximately 1.6 hours in all considered cases, which confirms the practical relevance of the proposed power adaptation mechanism. The highest gains are observed for low values of N_{RB}, especially when $N_d = 1100$, showing that the proposed scheme is particularly effective under resource-constrained and ultra-dense conditions. As N_{RB} increases, the gain slightly decreases and then stabilizes, revealing a diminishing-return effect when resource availability becomes less critical. In addition, the larger gains obtained at higher densities confirm the suitability of the proposed approach for interference-limited 5G-NR environments. Although the gain does not evolve monotonically with N_{RB}, such fluctuations are consistent with the stochastic and interference-coupled nature of dense wireless systems.

4.3. Energy efficiency

Energy efficiency is adopted as a key performance metric for the considered battery-constrained IoT network. In wireless communication systems, EE is commonly defined as the amount of successfully transmitted information per unit of consumed energy, or equivalently as the ratio between the achievable throughput and the total power consumption [31, 32]. Since practical IoT devices operating in 5G-NR networks consume energy not only through RF transmission but also through essential device circuitry, sensing, processing, control operations, and radio activity states [26, 27], the denominator of the proposed EE metric includes both a static operational power component and a transmission-dependent component.

Thus, considering the adopted device-level energy consumption model, the system energy efficiency is expressed as:

$$EE = \frac{\sum_{d=1}^{N_d} R_d}{\sum_{d=1}^{N_d} (P_{\text{base}} + DC \cdot \eta \cdot P_d)}. \tag{26}$$

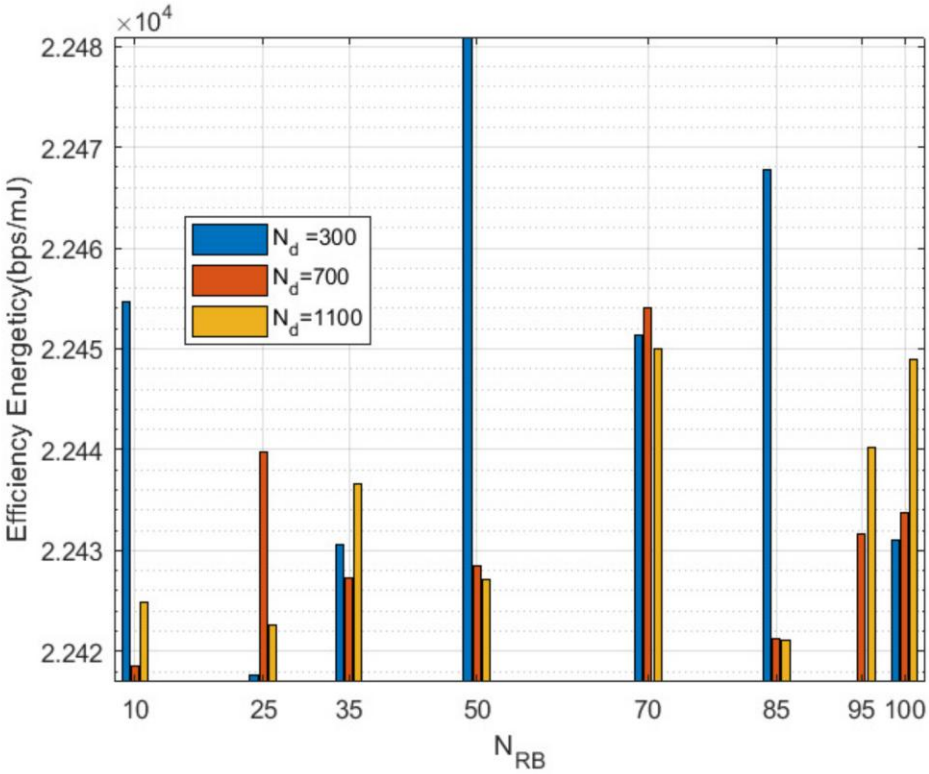

Figure 7. Energy efficiency.

Fig. 7 depicts the energy efficiency achieved by the proposed algorithm as a function of the number of RBs N_{RB} for three IoT densities, namely $N_d = 300$, 700, and 1100. Overall, the obtained energy efficiency remains confined to a narrow interval, approximately from 22.418 kbps/mJ to 22.481 kbps/mJ, which indicates globally stable and robust behavior of the proposed scheme over the considered resource configurations. The highest value is observed for $N_d = 300$ at $N_{RB} = 50$, where the energy efficiency reaches nearly 22.481 kbps/mJ. Other high values are also obtained for $N_d = 300$ at $N_{RB} = 85$ and for $N_d = 700$ at $N_{RB} = 70$, with energy efficiencies close to 22.468 kbps/mJ and 22.454 kbps/mJ, respectively. For the densest case, $N_d = 1100$, the energy efficiency remains slightly lower but still highly competitive, reaching about 22.450 kbps/mJ at $N_{RB} = 70$ and nearly 22.449 kbps/mJ at $N_{RB} = 100$.

A first important observation is that the variations across N_{RB} remain very limited, with a total spread of less than 0.3% between the minimum and maximum values. This result is particularly significant, as it shows that the proposed SoC-aware resource allocation strategy preserves its energy efficiency performance even when the amount of available radio resources changes substantially. In other words, the algorithm does not rely on a specific operating point to remain energy efficient, which is a strong indicator of robustness. Another relevant point is that the best energy-efficiency values are not systematically associated with the largest values of N_{RB}. Instead, local peaks appear around intermediate or moderate resource levels, such as $N_{RB} = 50$ and 70, suggesting that the balance between throughput enhancement and power reduction is not purely monotonic. This behavior is physically consistent with dense interference-coupled systems, where the marginal benefit of additional resources depends on both interference conditions and the resulting transmit-power adaptation.

Furthermore, the relative proximity of the curves for $N_d = 300$, 700, and 1100 indicates that the proposed method scales well with network density. Although slight differences are observed, especially at $N_{RB} = 50$ and 85, the energy efficiency does not collapse as the number of IoT devices increases.

This confirms that the proposed algorithm is able to maintain a favorable throughput-to-energy ratio even in ultra-dense deployments. Overall, these results demonstrate that the proposed SoC-aware scheme achieves not only high energy efficiency but also remarkable stability and scalability across a broad range of resource availability and device densities.

The proposed SoC-aware resource allocation and power control scheme significantly improves energy efficiency by jointly optimizing transmission power and resource usage. First, the substantial reduction in transmit power (from 23 dBm to approximately 7.78 dBm) directly decreases RF energy consumption. Second, by incorporating the SoC into the decision process, the algorithm prevents low-energy devices from engaging in inefficient transmissions, thereby avoiding unnecessary energy expenditure.

5. Conclusion

This paper proposes a SoC-aware heuristic radio resource allocation and power control framework for ultra-dense IoT communications underlying a 5G-NR cellular network. In contrast to conventional fixed-power schemes, the proposed approach explicitly incorporates the battery state of IoT devices into the resource allocation process, jointly with interference conditions, channel quality, and QoS requirements. This design enables a more realistic and energy-aware transmission strategy, particularly suited to battery-constrained massive IoT environments.

To address the high complexity of the considered optimization problem, a scalable low-complexity heuristic algorithm was developed. The proposed scheme remains computationally affordable for dense deployments while preserving practical scalability for large numbers of IoT users.

Simulation results demonstrated the effectiveness of the proposed framework. Compared with the considered benchmark, the proposed scheme achieves a stable throughput improvement of about 10–11%, while maintaining a high level of fairness, with a Jain fairness index close to 0.95 across all investigated scenarios. At the same time, the average IoT transmit power is significantly reduced from the fixed benchmark value to a much lower optimized level, which translates into a measurable battery lifetime gain exceeding 1.6 hours and consistently high energy-efficiency performance.

These results confirm that the proposed SoC-aware strategy simultaneously improves throughput, preserves fairness, reduces transmit power, and enhances battery sustainability without compromising scalability. Overall, this work demonstrates that integrating SoC into IoT resource allocation decisions provides an effective and practical solution for interference-limited ultra-dense 5G-NR environments.

Future work will focus on distributed implementations, more realistic battery and traffic models, mobility-aware scenarios, and learning-based adaptive power control strategies for B5G/6G IoT systems.

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