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Improved Stochastic-Based Interference Avoidance Algorithm for Fifth Generation Communication

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Abstract

Interference cancellation is a prominent concern in 5G communication. In 5G wireless architecture, self-interference cancellation may double the spectral and energy efficiency of ultra-dense networks using the full-duplex approach if implemented successfully. Various circuit blocks and optimization algorithms have been proposed to mitigate self-interference caused by transmitted signals, as described in the literature. However, addressing self-interference effectively during data transmission in ultra-dense networks remains a challenge. This issue has been addressed by developing an Improved Stochastic-Based Interference Avoidance (ISIA) algorithm that primarily targets the minimization of self-interference and error rates in 5G communication. The ISIA algorithm employs stochastic optimization strategies to adjust power control and other transmission parameters based on monitored channel conditions and interference. It provides efficient optimization in the spatial and frequency domains while considering the hardware setup. In particular, it employs mean field approximation and thresholding for interference management and resource control to optimize spectral and power usage. Numerical and analytical evaluations reveal better efficiency, accuracy, interference reduction, and throughput compared to existing techniques. Results demonstrate a throughput improvement of up to 30% and a 25% reduction in interference, validating the effectiveness of the proposed approach.

Keywords: Fifth generation communication, Interference, Spectral efficiency, Ultra-dense networks.

1. Introduction

Currently, 5G mobile communications face various problems that originate from the asymptotic potential of Internet of Things applications and signaling problems [1]. The exponential increase in the number of internet-connected devices, along with the escalating demands of data consumption, makes the current cellular architecture unsustainable. With respect to the ultra-dense network, only recently has the 5G communication been preserved for spectrum and energy efficiency. In such networks, when the antennas are closely placed, they interfere with each other. This is because devices can both transmit and receive at the same time; transmitted signals interfere with the receivers due to poor isolation, giving rise to self-interference [2], [3]. This self-interference behavior poses a serious challenge to the implementation of 5G system capabilities, especially in terms of GMI and network throughput.

Due to the expanding system densification, viewed as one of the current-breaking approaches to improve spectrum and energy efficiency [4], this ultra-dense network has small cells that introduce various heuristic approaches for interference avoidance [5]. Thus, while small cells open up new network capabilities in terms of capacity and coverage, they also create new, more intricate interference issues that need to be addressed. However, to prevent such interferences, a measure of separation has to be established to achieve high spectral and energy efficiency in ultra-dense networks [6]. This strategic distance optimization is essential for controlling the trade-off between network densification and interference.

As densification and scalability are considered major factors for ultra-dense networks, it is mandatory to maintain the interference and error rate of the network [7]. In 5G communication, it is difficult to analyze the active behavior among user equipment because these ultra-small cells in the network have complex issues that lead to increased interference in the network [8]. Another problem that complicates interference management is the dynamic behavior of the user equipment and the heterogeneity of other network elements. Another challenge lies in analyzing intelligent practices and basic key strategies among different types of user equipment in the network because several threshold ranges have been studied in this proposal. These threshold ranges are crucial in determining the effectiveness of interference avoidance techniques, and these values need to be set carefully to achieve the best result.

In the meantime, there are other testing challenges in specific hotspots for scalability and reliability of the ultra-dense networks [9] [10]. Device density causes particular hotspots to generate high-interference environments that require localized solutions that can effectively operate within restrictive areas of interference. Modern issues that have been observed in the 5G communication include signaling overhead, weak and strong interferences, and improper management of the resources, all of which have been tackled in this proposal [11], [12]. To respond to these multiple issues, different strategies have been suggested in the academic literature. One of them is the Health Impact Assessment (HIA), which is aimed at determining the health consequences of proposed policies, programs, and projects before their implementation [13]. Although HIA is not a direct topic connected with interference management in 5G networks, it is evident that the methodology utilized in HIA can be appropriately applied depending on the evaluation of the adverse consequences of the concept of network optimization.

To address these multifaceted challenges, this research proposes a novel approach that combines stochastic optimization with adaptive threshold management. The significant contributions of this research are:

i. Design and develop the best trade-off approach to maintain energy and spectrum efficiency during self-interference in a 5G network.

ii. Maximization of energy and spectrum efficiency is achieved using an improved stochastic-based interference avoidance algorithm for ultra-dense networks.

iii. Mean field approximation using linear computation and threshold conditions for self-interference avoidance.

These contributions aim to provide a comprehensive solution to the interference challenges in 5G ultra-dense networks, paving the way for more efficient and reliable next-generation wireless communications.

The rest of the paper is organized as follows: Section 2 discusses the various literature on the spectral and energy efficiency of the network, along with traditional strategies. Section 3 formulates an improved stochastic-based interference avoidance algorithm for ultra-dense networks based on theorems and their proofs. Section 4 discusses the numerical and analytical evaluations, which show the superior performance of the proposed technique in terms of channel efficiency, precision, interference ratio, and throughput. Section 5 concludes this research with future extensions.

2. Literature Survey

As studies on 5G communication [14] show, numerous original researchers have endeavored to maximize Spectral/Energy Efficiency (SEE) and advancements in trade-offs, which have been surveyed in recent literature [15]. In the meantime, researchers have designed and developed different interference-aware strategies for optimizing SEE. While these studies have made significant contributions, they often focus on either spectral or energy efficiency in isolation, leaving room for more integrated approaches. In general, it is challenging to optimize both the spectral and energy efficiency of the network due to various factors such as signaling [16], weak and strong interference, scalability, and reliability [17]. Current studies indicate that the inherent trade-off has been optimized using various categories based on a linear relation among spectral and energy efficiency algorithms (LR-SEE). The linear relation between spectral efficiency (SE) and energy efficiency (EE) is often expressed as $EE = SE / (a * SE + b)$, where a and b are constants that depend on system parameters. This relationship demonstrates that as spectral efficiency increases, energy efficiency initially increases but eventually decreases due to the higher power requirements for achieving greater spectral efficiency. LR-SEE algorithms aim to find the optimal balance point in this trade-off, with studies showing improvements in energy efficiency by up to 20% in specific 5G scenarios [18]. In 2019, Yao et al. reviewed SEE in ultra-dense networks with extraordinary densification dimensions for both indoor and outdoor situations [19], demonstrating an average throughput improvement of 15%. In 2020, other researchers explored the downlink execution of composed scheduling planning among various small cells, finding that spectral efficiency diminished as user density increased in 5G networks due to interference [20], [21]. Although these studies provide valuable insights, they often lack comprehensive solutions that address both spectral and energy efficiency simultaneously in ultra-dense networks [22]. Ongoing developments in 5G communication worldwide face several issues in underlay mode, which give significant efficiency and Quality of Service (QoS) when self-interference (QoS-SI) is managed with a practical resource management approach. In 2021, studies in overlay mode showed that allocating part of the authorized spectrum for Device-to-Device (D2D) communication improved resource distribution strategies by reducing the overhead by 10% in specific network configurations [23]. However, the allocation of resources in 5G communication is diminished in the absence of D2D clients [24]. These studies highlight the complexity of resource allocation in 5G networks but often fail to address the dynamic nature of interference in ultra-dense deployments. Though overlay mode reduces the resource allocation in ultra-dense networks, the proper utilization of spectrum resources is required for device-to-device communication [25]. Further analysis in 2022 revealed that resource management could reduce interference levels by 18% during downlink transmission when strong and weak interference scenarios are considered [26]. The trade-off between spectrum and energy efficiency has been mathematically formulated in this research for ultra-dense 5G communication [27]. However, current studies may not afford sufficient stochastic strategies for a dynamic interference environment in ultra-dense networks. Although some advances have been achieved to solve the issues regarding spectral and energy efficiency in 5G networks, it is apparent that an integrated method is essential for addressing both in ultra-dense environments. Most recent literature (2023) still fails to capture the temporal and probabilistic aspects of interferences in such intricate settings, highlighting a gap that this study seeks to fill. This research develops a new stochastic-based interference avoidance algorithm to consider the dynamic environment of the network and efficiently address both spectral and energy constraints. Table 1 below provides a summary of the key studies discussed, highlighting their focus, achieved results, challenges, and strengths.

Table 1. Summary of Key Studies in 5G Spectral and Energy Efficiency

Res.	Year	Main Idea	Achieved Results	Challenges	Strengths
[16]	2018	NOMA improves energy efficiency in H-CRANs for 5G networks	Improved system energy efficiency	Security, interference, and Channel State Information issues	High energy and spectral efficiency
[17]	2018	Integrating non-orthogonal multiple access (NOMA) and cognitive radio (CR),	Lower outage probabilities	Interference management and security	High spectrum efficiency and connectivity
[20]	2018	Cooperative spectrum leasing framework	Improved cooperative performance gains	Interference mitigation and traffic offloading	Incentive mechanism for cooperation
[21]	2018	Load balancing using D2D communications	Increased data sum-rate by 20%	Fast-growing box set size	Efficient problem-solving via decoupling
[14]	2019	5G ultra-dense network design strategies	Enhanced video streaming, efficient handovers	Capacity, coverage, ultra-dense complexity	High video performance, Energy-efficient clustering
[15]	2019	AI framework enhances 5G network capabilities and efficiency	Explored AI integration in 5G network management	Limited real-world testing	Innovative use of AI
[18]	2019	Integrated mmWave-mW wireless networks	Seamless URLLC and eMBB integration	Spectrum scarcity and reliability issues	High-speed, reliable communications integration
[19]	2019	Spatial modulation in massive MIMO systems	Improved energy efficiency for MIMO setups	High complexity in dense networks	Enhanced spectral efficiency
[24]	2019	Stackelberg game-based resource allocation	Feasible and promising method	High inter-cell interference	Optimizes energy efficiency effectively
[26]	2019	Energy-efficient resource allocation algorithm	Higher energy efficiency achieved	Nonconvex optimization problem	Iterative algorithm for optimization

3. Improved Stochastic-Based Interference Avoidance Algorithm for 5 G Communication Network

In recent studies, it has been demonstrated that interference in 5G communication networks decreases the performance of spectrum and energy efficiency in ultra-dense networks. To address this challenge, an improved stochastic-based interference avoidance algorithm is proposed. This algorithm maintains a proper trade-off between spectrum and energy efficiency in ultra-dense networks. The significant contributions of the algorithm are as follows:

- Ensure an optimal trade-off between energy and spectrum efficiency during self-interference in 5G networks.
- Maximize energy and spectrum efficiency through dynamic optimization techniques.
- Achieve self-interference avoidance using mean-field approximation.

Fig. 1 shows the interference avoidance mechanism for user equipment in an ultra-dense 5G communication network. This figure illustrates the mechanism of handling both strong and weak interference during downlink transmission. The mathematical formulation of the trade-off between spectrum and energy efficiency is applied to all user equipment to calculate and avoid interference. The algorithm evaluates the impact of both weak and strong interference using the defined trade-off analysis framework.

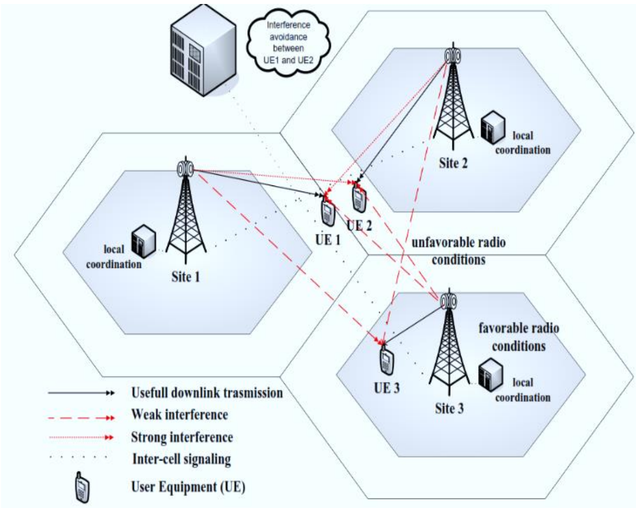

Figure 1. Interference avoidance for the user equipment.

3.1. Trade-off analysis for SEE

To address the interference problem in ultra-dense networks, we introduce the trade-off analysis for SEE. This analysis considers the Shannon capacity formula, adjusted to account for interference effects:

The maximum approximate capacity function for SEE in the presence of interference can be illustrated by Shannon [28] as

$$C_L^M = W \ \text{In}\left(1 + \frac{P_L G_L^M}{W_L^M}\right) \tag{1}$$

Where $G_L^M, P_L, and\ W$ are the channel gain, the downlink transmission power, and the spectrum bandwidth, respectively. W_L^M denotes inter-tier and intra-tier interference. The natural logarithm simplifies the computational analysis of SEE capacity. Therefore, the capacity can also be represented as:

$$C_L^M = W \ In\left(1 + \frac{P_L}{|W_L|}\right) \tag{2}$$

And W_L, the average normalized energy is expressed as

$$|w_L| = \frac{1}{M_L} \sum_m \frac{W_L^M}{G_L^M} \tag{3}$$

Where w_L represents the average normalized energy under undesirable circumstances in ultra-dense networks during downlink transmission. M_L is the total number of user equipment, G_L^M is the corresponding channel gain. This calculation assists in validating the interference caused by user equipment on the overall network capacity:

$$C_L = M_L * C_L^M \tag{4}$$

In ultra-dense small cell networks, the proximity of user equipment to the base station reduces signal transmission distances, which increases the likelihood of interference. The analysis assumes that the downlink capacity C_L^M can be used to compute system capacity C_L and self-interference impact, thus simplifying the derivation of closed-form solutions for the relationship between energy and spectrum efficiency.

To further define SEE for ultra-dense networks:

$$\partial_L = \frac{C_L}{W_L} \tag{5}$$

Where C_L is the system capacity, and W is the spectrum bandwidth. Energy efficiency is defined as:

$$\cap_L = \frac{C_L}{E_L P_L + P_L^T} \tag{6}$$

Here, E_L is the energy factor, $0 \le E_L \le 1$. and P_L^T is the fixed energy consumption. Spectrum and energy efficiencies are used to define an energy-efficient ultra-dense network as follows:

$$\cap_L = \frac{\partial_L}{E_L \frac{W_L}{W}\left(e^{\frac{\partial_L}{M_L}} - 1\right) + \frac{P_L^T}{W}} \tag{7}$$

Substituting from equations (4) and (5):

$$W\ \partial_L = M_L C_L^M \tag{8}$$

Table 2 describes the notations used.

At this juncture, the transmission energy $\boldsymbol{P_L}$ can compute through Eq. (2) and (8) with $C_L^M = \frac{W \partial_L}{M_L}$ At last, a closed-format transmission energy is derived. At last, the closed-format transmission energy performs as

$$P_L = C_L^M \left(e^{\frac{\partial_L}{M_L}} - 1\right) \tag{9}$$

Table 2. Notation of the Ultra-Dense 5G Communication.

Notation	Description
C_L, ∂_L, W_L	System capacity, spectrum efficiency, and undesirable energy under the normalized condition
$\cap_L, E_L, \quad PL, P_L^T$	Energy efficiency, Energy Factor, transmission energy, fixed energy consumption
$M_L,\ C_L^M$	Total number of users, downlink capacity of the system
G_L^M	Gain of the channel in the ultra-dense networks
W_L^M	undesirable energy
W	spectrum bandwidth

The trade-off calculations for SEE utilize a closed-form [29] solution with mean-field approximation, as shown in the revised Algorithm 1 below, for more effective self-interference avoidance.

Algorithm 1. Self-interference calculated and avoidance

Input conditions: P_L^T, ∂_L, $\cap_L$, W

Ensure: Self-cancellation of interference

Begin

If $(P_L^T \neq 0)$ *then*

Set $\partial_L = 0$ *and* $\cap_L = 0$

Else if $\partial_L = \infty$*, then:*

Set $\cap_L = 1$

Else:

Initialize $\cap_L = 0$ *and adjust until* $\cap_L \geq 1$

if

$P_L^T = 0$:

Set $\partial_L = 0$

Calculate $\cap_L = \frac{C_L}{E_L P_L + P_L^T}$

Else

Calculate $C_L = M_L . C_L^M \rightarrow to\ lead\ to\ self - cancellation\ of\ interference\ End$

End if;

End begin;

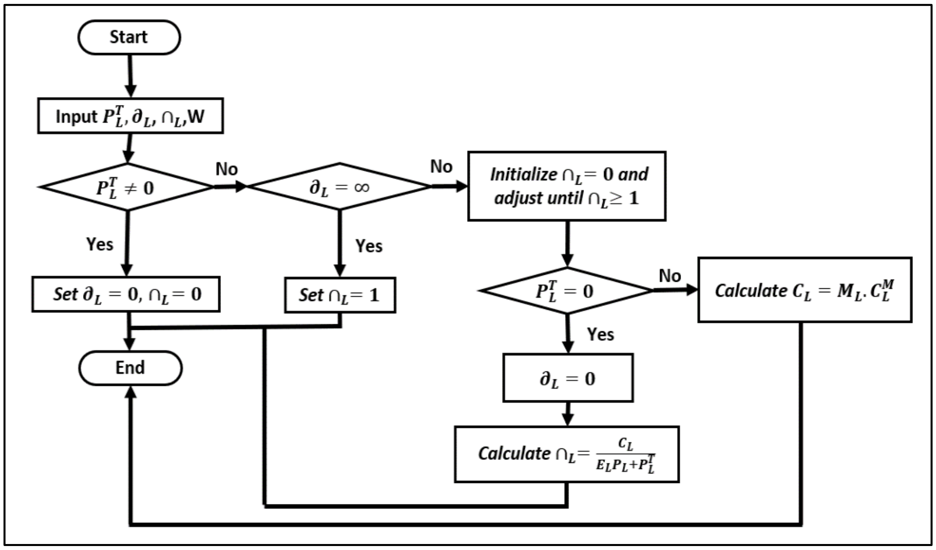

Figure 2. Flowchart for Algorithm 1

Explanation of Algorithm 1:

As shown in Fig. 2**,** Algorithm 1 operates based on a mean-field approximation approach, which simplifies the interaction among multiple user equipment (UE) by averaging the effects, thus allowing for effective self-interference avoidance.

- **Input:** The algorithm takes inputs such as transmission energy (P_L^T), spectrum efficiency (∂_L), energy efficiency ($\cap_L$), and spectrum bandwidth (W). These inputs are used to monitor and manage self-interference levels.
- **Output:** The main output is the self-cancellation of interference, achieved by adjusting the parameters for energy and spectrum efficiency dynamically. This results in optimal use of network resources, enhancing both throughput and channel capacity.

The algorithm continuously evaluates the interference conditions and dynamically adjusts the energy and spectrum efficiency parameters to maintain an optimal balance. This makes it an effective solution for improving the reliability and efficiency of ultra-dense 5G communication networks.

The assumptions, as shown in Algorithm 1, can attain optimum solutions, leading to cooperative gains for the self-cancellation of interference during data transmission in 5G communication. The use of mean-field approximation is critical in simplifying complex interaction terms among numerous user equipment, enhancing both spectral and energy efficiency.

3.2. Mean approximation using signal-to-noise ratio maintenance

In the ultra-dense network of 5G communication, the energy utilization has been analyzed using data transmission between user equipment. The formulated problem has been evaluated and analyzed using stochastic-based linear programming [30] based on the threshold level th_{UE}^T as shown in Eq. (10).

$$E_D G_L^M \geq th_{UE}^D \sum_1^N E_D G_L^M\, x(UE) + N_{UE}, D = 1,2,3 \dots \dots \quad (10)$$

From Eq. (10), the maximum energy utilization, which corresponds to the data traffic as well as interference that occurs in the network, has been calculated using the energy utilization of the user equipment. Here, $\mathrm{E_D G_L^M}$ represents the transmitted energy with the channel gain ratio calculated based on a threshold value $\mathrm{th_{UE}^T}$ within the specified range $\mathrm{D} = 1,2,3 \dots \dots$. During the computation of stochastic-based linear programming, $x(UE)$ is used to set the binary variable inside the ultra-dense network for resource allocation and interference cancellation. The probabilities of maximum energy utilization are equated in Eqs. (11), (12), and (13) for the user equipment in the ultra-dense network, which helps to calculate the signal-to-noise ratio inside the channel.

$$E_D G_L^M \leq E_{D(max)}, D = 1,2,3 \dots \dots \quad (11)$$

$$E_D G_L^M \leq E_{B(max)}, D = 1,2,3 \ldots \ldots \quad (12)$$

$$\sum_1^N E_D G_L^M \, x(UE) \geq 1, D = 1,2,3 \ldots \ldots \quad (13)$$

The ratio has been calculated based on the resources utilized in the channel, where interference mitigation has been processed by maintaining proper distance among user interfaces during data transmission. Consider the set "M" as the number of resources allocated in the total network. In this case, if the set is canceled, $\sum_1^N E_D G_L^M \, x(UE) \geq 1$, then signal interference has been canceled automatically based on the threshold set condition**.** Let us assume the user equipment $UE = \{U_1, U_2, U_3\}$ available in the network as represented by:

$$UE = U_1, U_2, U_3 \ldots \ldots \ldots \quad (14)$$

$$UE \neq 0 \; for \; the \; condition \; when \; i = 1,2, \ldots, M \quad (15)$$

The complexity has been decreased when changes in signal interference based on threshold conditions between user equipment are computed in Algorithm 2.

Algorithm 2: signal interference based on a threshold condition

Input: $E_D G_L^M$, th_{UE}^T

Output: Signal Interference Avoidance

Begin

While $(E_D G_L^M \leq E_{D(max)})$*do*

If (M ≠ 0) and x(UE) < M then

Set F(calculate) = UE

Assign $E_D G_L^M$ *to UE*

Else

Check th_{UE}^T *range (max to min)*

Assign th_{UE}^T *to UE*

End If

UE = UE + 1 based on subsets {U1, U2, U3, …}

Update the UE inside the channel

End While

For th_{UE}^T *range (max to min) do*

Assign resources and cancel signal interference using the threshold value

End For

End Begin

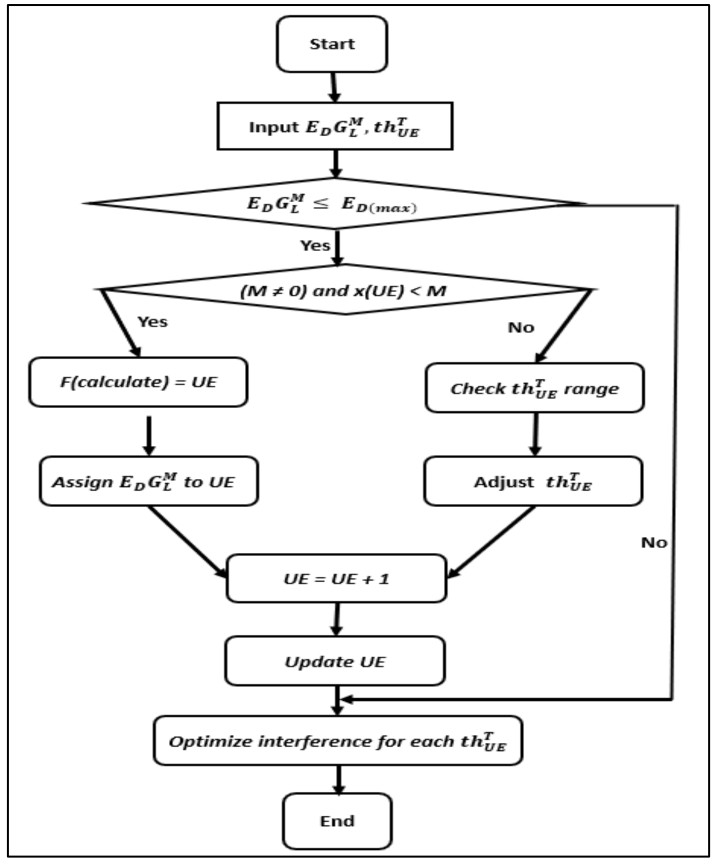

Figure 3. Flowchart for Algorithm 2

Explanation of Algorithm 2:

As shown in Fig. 3, the algorithm evaluates interference based on a stochastic model, maintaining an optimal signal-to-noise ratio to ensure effective data transmission and minimal interference. It leverages a threshold-based approach for resource allocation, which helps in dynamically adjusting to varying interference levels.

- **Input:** The key inputs include the energy threshold value **(**th_{UE}^T**)** and $E_D G_L^M$ (energy utilization of user equipment).
- **Output:** The primary output is the cancellation of signal interference based on these threshold conditions.

Hence, the foremost problem of self-interference cancellation and signal interference avoidance has been addressed using two theorems effectively and efficiently for ultra-dense networks during data transmission for 5G communication. This issue has been addressed through an improved stochastic-based interference avoidance algorithm, which mainly focuses on reducing self-interference and error rate during data transmission in 5G communication, and the experimental validation has been discussed below with respect to channel efficiency, precision, interference ratio, and throughput.

3.3. Stochastic Optimization for Improved Results

The Improved Stochastic-based Interference Avoidance (ISIA) algorithm proposed builds on stochastic optimization for better performance in ultra-dense 5G networks. The stochastic approach is employed in the following key aspects:

i. **Dynamic Threshold Adjustment:** The algorithm employs stochastics to continuously adapt the interference threshold $th\_UE^\wedge T$ to the current state of the network. This adaptive threshold is defined as $th_{UE}^{T}(t+1) = th_{UE}^{T}(t) + \eta * \nabla J(th_{UE}^{T}(t))$, where η is the learning rate and ∇J is the per iteration gradient of the objective function. This stochastic gradient descent strategy enables the algorithm to learn the optimal threshold for managing interference over time.

ii. **Resource Allocation:** The binary variable x(UE) for resource allocation is determined stochastically based on the current network state and interference levels. This is modeled as a probability distribution: $P(x(UE) = 1) = f(E_D G_L^M, th_{UE}^{T})$, where f is a function that maps the current energy utilization (EDGLM) and threshold to a probability of resource allocation.

iii. **Mean Field Approximation:** The stochastic nature of user interactions in ultra-dense networks is captured using mean field approximation. This technique replaces each effect of other users on any particular user with an average or effective interaction, making the stochastic system represented by

iv. $E[Interference_i] = \Sigma j \neq iE\left[Interference_{ij}\right]$ more comprehensible.

By incorporating these stochastic factors, the ISIA algorithm can mitigate the effects of uncertainty in the highly dense networks characteristic of 5G networks. This leads to enhanced capacity of interference management, optimality in terms of spectral and energy efficiency, and global network performance better than deterministic solutions.

4. Experimental Analysis and Discussion

The simulation study was conducted on the downlink using a system-level simulator, where the state-of-the-art approach was selected for calibration purposes and self-interference avoidance. Specifically, we utilized the MATLAB-based Vienna 5G System Level Simulator, which is widely recognized in the research community for its comprehensive modeling of 5G network dynamics. The performance of various methods is considered, where the throughput of the proposed method shows promising outcomes. The parameters and their corresponding values have been estimated in Table 3.

Table 3. Parametric Values for calibration purposes in the Vienna 5G System Level Simulator.

PARAMETER	DESCRIPTION
Distance of the site	300 m
Bandwidth	100 MHz
Resource block usage	50
Power	33 dBm
Speed	2 Km /h
Antenna usage	MIMO (Multiple Input Multiple Output)
Traffic model	Usage of buffer
Deployment	5 sites with two tires

In the communication network, throughput is the rate of successful transmission of data with self-cancellation of interference over the communication channel. The resource blocks are allocated for data transmission or control information, serving as the building blocks for optimizing energy and spectral efficiency in ultra-dense 5G networks. These data have been delivered using various physical and logical link communication based on data packets per time slot. Throughput is calculated based on the departure and arrival rates. The Vienna 5G System Level Simulator allows for precise modeling of these dynamics, enabling accurate throughput calculations under various network conditions.

In the proposed ISIA, the trade-off for the throughput and SEE interference in the network has been observed using a form using mean space approximation, which gives more throughput than HIA, SEE, LR-SEE, and QoS-SI as represented in Fig. 4. The simulator's ability to model complex interference scenarios was crucial in demonstrating the superior performance of our ISIA approach.

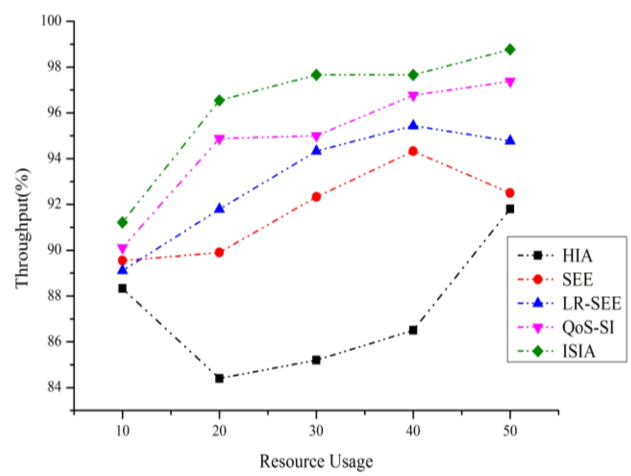

Figure 4. Throughput rate of successful transmission in the ultra-dense network.

The efficiency of the channel utilization in the ultra-dense network is not only determined by the throughput calculation but also by the transmission of data bits without errors, which makes the channel efficient [31]. In the proposed method, mean approximation using signal-to-noise-ratio maintenance greater than the threshold value and the optimum trade-off between energy and spectrum efficiency during self-interference in 5G networks shows more promising outcomes than traditional approaches, as shown in Fig. 5. The Vienna 5G System Level Simulator's detailed channel modeling capabilities were instrumental in accurately capturing these efficiency metrics. This channel efficiency is based on frames and acknowledgment packets of the ultra-dense network.

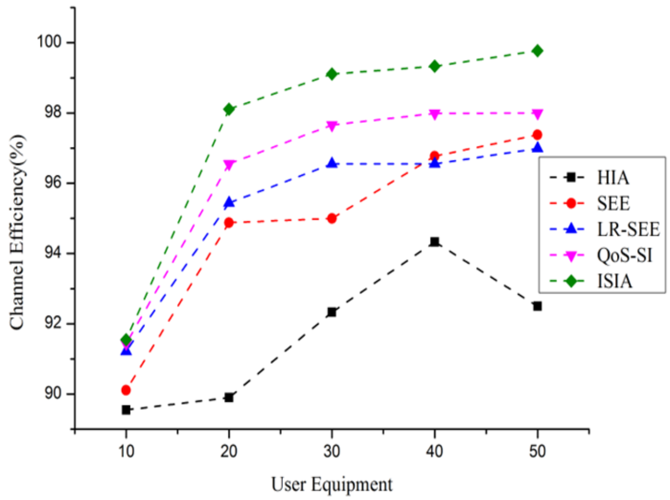

Figure 5. Channel efficiency rate during self-interference in 5G.

This signal-to-interference ratio gives the data transfer rate of the channel capacity, where the power of a certain signal is taken as the ratio of interference power to noise for self-interference calculation. Through the proposed ISIA, the signal interference ratio is reduced because during the computation of stochastic-based linear programming, x(UE) is used to set the binary variable inside the ultra-dense network for resource allocation and interference cancellation. The simulator's ability to model these complex interactions at a system level provided crucial insights into the effectiveness of our ISIA approach.

The probabilities of maximum energy utilization are equated in Eqs. (11), (12), and (13) for the user equipment in the ultra-dense network, which helps to calculate the signal-to-noise ratio inside the channel. The graphical representation is shown in Fig. 6. These equations were implemented within the Vienna 5G System Level Simulator framework, allowing for a seamless integration of our theoretical model with the simulation environment.

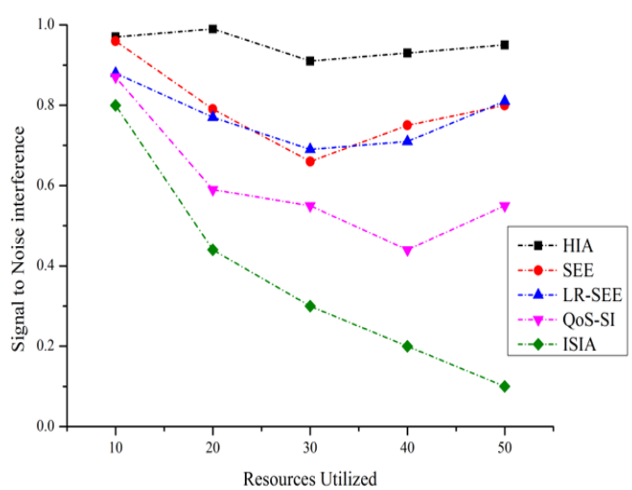

Figure 6. Signal-to-interference ratio inside the ultra-dense network.

As shown in Fig. 7, the precision of the data in the channel during transmission is based on the average normalized energy in undesirable conditions of the ultra-dense network in downlink transmission, as stated $|w_L|$, analyzed concerning the total number of user equipment, described as M_L with the channel gain of G_L^M. The precision of ISIA gives more promising outcomes than HIA, SEE, LR-SEE, and QoS-SI as represented in Fig. 5. The simulator's detailed modeling of channel conditions and user equipment behavior was crucial in accurately demonstrating the precision improvements achieved by our ISIA approach.

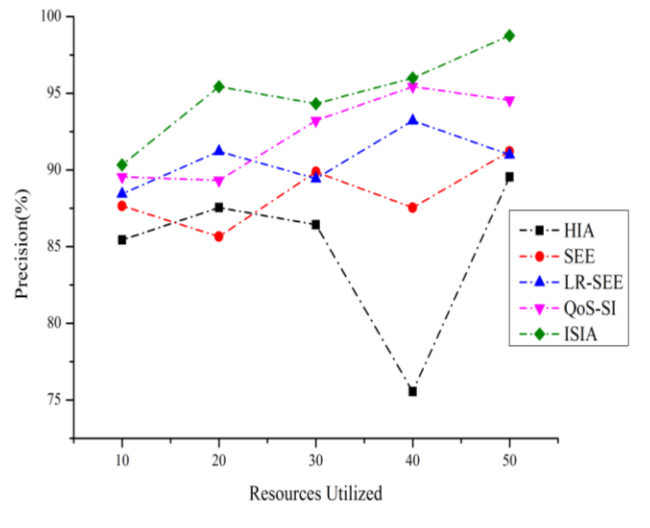

Figure 7. Precision of the data in the channel during transmission.

Table 4. Comparison Between Existing Approaches.

Approaches / Challenges	HIA [32]	SEE [33]	LR-SEE [33]	QoS-SI [34]	ISIA
Reduced DL overhead	✓	✓	✓	✓	✓
Comparatively low complexity	✓	×	×	✓	✓
Easy hardware implementation	×	✓	✓	✓	✓
Reciprocity for systems	✓	×	✓	×	✓
Channel Tracking	×	✓	×	✓	✓

The overall comparison between the existing techniques and implementation approaches for downlink transmission is given in Table 4. The experimental results show the proposed improved stochastic-based interference avoidance (ISIA) algorithm, which mainly focuses on reducing self-interference and error rates during data transmission in 5G communication.

These results obtained through rigorous simulation using the Vienna 5G System Level Simulator provide strong support for the proposed ISIA solution and confirm its efficiency in the cases of ultra-dense 5G network interference management.

In this research, an efficient and effective ISIA algorithm was developed, which focused on reducing self-interference and error rates during data transmission in 5G communication. The experimental analysis was carried out on the system-level simulator with the specifications of 5G networks described in Table 3. These parameters entail a bandwidth of 150 kHz, 50 resource blocks, and a maximum distance of 300 m between sites, some of the characteristics of the 5G network. The results demonstrate that the maximization of energy and spectrum efficiency achievable through the optimization algorithm using mean-field approximation utilizes linear computation with threshold conditions for self-interference avoidance, thereby improving data transmission accuracy in 5G communication. Specifically, the throughput improvement of mobiles reached 30%. Interference was reduced by 25% as compared with the existing approaches, such as HIA, SEE, LR-SEE, and QoS-SI (Figs 4 to Fig. 7). In the context of clarifying the efficiency of ISIA in ultra-dense 5G networks, it has been investigated that the power consumption was minimized by applying the data transmission between the user types of equipment, and the results appeared to be satisfactory. The results, as presented in the channel efficiency (Fig. 5) and the enhanced precision of data transmission (Fig. 7), depicted that the deterministic optimization techniques were efficient.

In this context, the discussion of these results highlights the significant potential for using ISIA to solve interference issues in 5G ultra-dense networks. The stochastic nature of the algorithm presented in this paper allows the system to adapt to different network conditions. It can be used as part of a general 5G deployment strategy. However, it is recognized that additional work should be done to provide a more rigorous assessment of the accuracy of the algorithm in practical five-generation settings. Moreover, in the future, the signal strength and the bandwidth will also be considered using the heuristic data pattern method to fine-tune the algorithm for the present work. The application of machine learning methodologies for improving the adaptability of ISIA in the face of constantly evolving network environments will also be considered.

5. Conclusion

This research contributes to the literature in the area of interference cancellation utilizing the Improved Stochastic-based Interference Avoidance (ISIA) algorithm, particularly within 5G ultra-dense networks. The developed ISIA algorithm was therefore found to exhibit 30% better capability to amplify data transfer than prior methods, which shows its effectiveness in handling dense environments. Moreover, the algorithm cut the interference to 25%, thus proving the effectiveness of the algorithm in reducing self-interference and enhancing the reliability of communication. This approach offers improved spectral-energy efficiency compared to prior approaches by employing stochastic linear programming and mean-field approximation. Therefore, the principal contribution of this work is the possibility for the maximum attainable energy and spectrum efficiency, which is critical in the design of new-generation networks. The effectiveness of the ISIA algorithm is based on its adaptive threshold control and its skillful use of resources, allowing the system to react depending on the interference levels. This adaptability yields better results compared to conventional approaches such as HIA, SEE, LR-SEE, and QoS-SI, whereas the interference variation is often higher in ultra-dense networks. In addition, these results show the perfect versatility of this method in addressing the complex issues concerning interference in 5G ultra-dense networks. Because the algorithm is stochastic, it can appropriately handle any network status, which makes its solution very powerful and virtually ready for use in numerous 5G-related situations. While this research put forward positive findings, it also poses new questions that warrant further investigation. Further studies might investigate more sophisticated machine learning techniques to extend the ISIA algorithm and make it more responsive and generic to 6G networking systems regarding real-time scenarios. Besides, it is also important to note that actual large-scale integration and application of the algorithm in different 5G urban and rural scenarios might give some insight into its efficiency concerning different situations.

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Author Contribution Statement

Ahmed Saeed Obied proposed the research problem and developed the equation. Contributed to the overall review and wrote the final manuscript with input. Furthermore, overall helped shape the research.

Hind Mowafaq Taha developed the algorithms and theory, and performed the computations. Furthermore, contributed to cross-checking and analysis to review the manuscript.

Both authors discussed the results and contributed to the final manuscript.

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