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Research article

# Dynamic resource allocation for energy-efficient downlink NOMA systems in 5G networks

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ABSTRACT

Non-Orthogonal Multiple Access (NOMA) is a promising energy-efficient technology designed to satisfy the demands of future networks by efficiently sharing radio resources. In NOMA, the same radio resource is simultaneously assigned to two users at different power levels based on the NOMA-power domain. Resource allocation in NOMA presents a non-convex challenge, characterized as a non-deterministic polynomial (NP-hard) problem. This involves user and channel assignment and power allocation, making it an extraordinarily complex task to achieve an optimal solution. In this work, Simulated Annealing (SA) is proposed as an optimization technique for resource allocation in an energy-efficient downlink NOMA system. This resource allocation scheme addresses user and channel assignment, as well as power allocation, using SA as an efficient standalone approach to maximize energy efficiency in NOMA. SA is utilized to execute the assignment of users to channels, distribute the necessary power for each channel, and determine the power ratio among users sharing the same channel. The results obtained demonstrate a significant improvement in energy efficiency, outperforming the existing numerical methods by 22 %. The proposed SA scheme not only achieves a close optimal solution but also in less computational time, offering sufficient reliability in terms of energy efficiency enhancement when compared to the existing numerical method.

## 1. Introduction

### 1.1. Preliminary

Mobile network development is rapidly expanding to meet the soaring demand for high data rates, massive connectivity, and increased communication devices in the network. The fifth generation (5G) network has emerged as a pivotal potential network, poised to fulfil the requirements for high data rate, spectral efficiency, and the ever-increasing number of devices, all within the constraints of limited radio resources, spectrum availability, and energy resources. The escalating number of devices has led to a surge in energy consumption; a major concern both economically and ecologically for wireless operators. Hence, the development of an energy-efficient communication system has become a critical metric in shaping the evolving architecture of cellular networks, often referred to as green communication [1,2]. In the context of 5G, the proliferation of devices and the demand for massive connectivity have placed greater emphasis on data rates and spectral efficiency, necessitating more power and bandwidth from the base station (BS). However, the availability of these precious radio resources remains constrained and challenging. Furthermore, the ability to

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accommodate users is restricted by the finite orthogonal channels within the cell's coverage area, leading to diverse power effects, power consumption, and heightened carbon dioxide ($CO_2$) emissions due to increased transmit power [3]. The constrained granularity of orthogonal resources in Orthogonal Frequency Division Multiple Access (OFDMA) imposes limitations on both the quantity of radio resources and the number of users. Consequently, the pursuit of an energy-efficient system is imperative for cellular networks, in consideration of the constraints imposed by radio resources and international network architecture standards [1–3].

Non-orthogonal multiple access emerges as a promising solution to meet the demands of the next network generation, primarily due to its superiority in achieving higher data rate, data balance, and energy efficiency. In the NOMA system, multiple users concurrently utilize the same frequency, code, or time slot, with each user being assigned distinct power levels in accordance with the power domain-NOMA principle. Within the NOMA system, the BS employs superposition coding (SC) to multiplex multiple users on the same channel, with successive interference cancellation (SIC) employed at the receiver to mitigate interference arising from radio resource sharing (RRS) [4,5]. To ensure an effective NOMA system, an efficient power allocation scheme must be devised to manage interference effectively. Energy efficiency (EE) presents an additional challenge within the NOMA system. It necessitates the efficient allocation of radio resources to strike a balance between power allocation and achieved data rates, all while maintaining a harmonized and acceptable energy consumption level. This paper explores prior research efforts on energy efficiency within the NOMA system in the following section.

### *1.2. Related work*

In [2], the authors formulated a fractional optimization problem to maximize energy efficiency based on sub-channel and power allocation, rate selection, and transmission scheduling for the downlink NOMA-power domain. They used duality theory in linear programming (LP) and employed a sub-gradient algorithm using the CPLEX optimization tool to numerically solve the LP problem. The objective was applied to reframe the optimization problem into a manageable fractional optimization problem while imposing constraints to restrict the maximum-to-minimum user data rate ratio. The authors concluded that two users on the same channel are the maximum number for energy-efficient downlink transmission NOMA. The results showed a close optimal solution based on an iterative algorithm that is better than the existing algorithms including, the Orthogonal Multiple Access (OMA) [2]. However, the system model in Ref. [2] employed certain assumptions and simplifications in the propagation model, assuming uniform channel gain, and interference considerations. These simplifications may not align perfectly with the complexities and variabilities encountered in practical mobile communication environments, potentially affecting the model's accuracy and applicability. Moreover, a power allocation and sub-channel assignment scheme was formulated in Ref. [6], employing the concept of the difference of convex (DC) optimization problem and a greedy approach to match users with sub-channels. This scheme aimed at maximizing energy efficiency in the downlink NOMA network, assuming perfect channel state information (CSI). Notably, the proposed algorithms demonstrated a superior energy efficiency compared to OFDMA. While the implementation of greedy user-channel matching and DC optimization showed effectiveness, it may not yield the optimal solution in complex network scenarios when accounting for imperfect CSI that mirrors the practical mobile network conditions. Similarly, the DC programming approach in Ref. [7] was proposed to optimize the power and bandwidth with the goal of maximizing energy efficiency in downlink NOMA. This system design considered the allocation of unequal sub-channel bandwidth to users. To transform the non-convex problem into an equivalent DC form, slack variables were introduced. Subsequently, an iterative algorithm was employed to solve the constrained concave-convex procedure. The proposed NOMA scheme exhibited enhanced EE performance compared to the NOMA with equal bandwidth and the conventional OFDMA. However, the method in Ref. [7] transformed the non-convex problem using slack variables might not fully encapsulate the complexities of mobile network conditions, where bandwidth allocation and user demands can be highly dynamic and unpredictable processes in NOMA. The authors in Ref. [8] proposed a joint resource allocation scheme based on a matching algorithm for user and sub-channel and power allocation based on Dinkelbach's algorithm to maximize the energy efficiency of a multi-carrier NOMA system (MC-NOMA). The proposed scheme converted the optimization problem into a series of sub-problems using the penalty function (PF) and achieved a superior level of performance compared to OFDMA and fractional transmit power allocation (FTPA). Therefore, the conversion of the optimization problem into sub-problems using the penalty function might oversimplify complex network dynamics, potentially reducing the applicability of the solution in more variable network scenarios. Furthermore, authors in Ref. [9] introduced a low-complexity numerical scheme for power allocation with the objective of optimizing the power for each user, thereby enhancing the EE in the downlink NOMA system. The results depicted an optimum performance of NOMA in terms of EE over the conventional OFDMA. A summary of the existing work is provided in the table below.

Al-Obiedollah et al. [10], proposed a resource allocation scheme based on Dinkelbach's to transfer the problem into convex form to maximize the energy efficiency in MC-CR-NOMA. The scheme was iteratively employed to achieve optimal energy efficiency, striking a balance between data rate and energy efficiency that also outperformed the existing schemes. Although the scheme outperformed the existing methods, its adaptability and performance in dynamic network conditions and user locations require further comprehensive evaluation. In Ref. [11], the authors transformed the optimization problem into an equivalent subtractive form, based on fractional programming (FP) with sequential optimization. This was complemented by a greedy sub-carrier allocation strategy to address the non-convexity of the power allocation for EE maximization in a downlink MC-NOMA. The proposed scheme demonstrated effective EE performance while maintaining low complexity. Maintaining low complexity using greedy sub-carrier allocation [11] may not assure global optimal solutions in diverse network environments. Despite the achieved solution, the sequential nature of the optimization could lead to computational inefficiencies, which might affect its efficacy across various network scenarios, especially in HetNet-NOMA. In Ref. [12], the authors derived a closed-form optimal solution for the power allocation, sub-channel and user assignment based on the bilevel programming method to minimize the energy consumption for the multi-user-multi-base station

NOMA network. The EE problem was formulated in a non-probabilistic form, achieving higher EE performance than the conventional OMA with less complexity than the exhaustive search methods. The approach applied in Ref. [12] may not sufficiently represent the dynamic nature of real-mobile networks, including variable channel fading. This could impact the practicality and reliability of the solution, especially in high-density networks with diverse data traffic demands. Alternatively, the authors proposed a resource allocation scheme based on DRL as three learning frameworks for energy efficiency maximization in uplink multi-user NOMA [13]. The discrete DRL method was designed for power allocation to enhance learning efficiency, reduce the output dimension, and address non-convexity issues. The scheme demonstrated improved EE performance with a reasonable computational consumption for uplink NOMA. However the method demonstrated enhanced energy efficiency with manageable computational demands, its scalability and real-time responsiveness in highly dynamic and densely populated network environments require additional investigation to fully ascertain its effectiveness and applicability, including Rician fading channel scenarios. In Ref. [14], a power allocation scheme and user clustering were proposed to maximize energy efficiency, utilizing Stackelberg game competition in multi-user and multi-cluster NOMA networks. The resources were allocated as revenue, and optimal power was determined based on the minimum transmission rate, along with sub-optimal clustering. This approach achieved an optimal sum-rate with lower computational requirements for the BS. While sub-optimal clustering reduced computational load and achieved optimal sum-rate [14], it could compromise user experience in dynamically varying network scenarios. Furthermore, the application of game theory in this scenario demands precise calibration to balance fairness and efficiency, especially in HetNet-NOMA environments. In Ref. [15], the authors developed an improved rider optimization technique for resource allocation to maximize energy efficiency based on M2M communication in NOMA. The proposed scheme showed an improved energy consumption in comparison to the existing schemes. Despite the effectiveness of this technique compared to existing schemes, further exploration is required to confirm its broad applicability and robustness, particularly under diverse and high-demand network conditions. Conversely, in Ref. [16], the authors adopted a space-time block code transmission scheme for spatial diversity increment and simultaneous wireless information and power transfer (SWIPT) for energy harvesting in the NOMA network. Further, the Nash bargaining concept was employed to ensure fair resource allocation, outperforming the existing approaches in terms of the achievable rate and energy efficiency. Moreover, the intricate balance of spatial diversity, information transmission, and energy harvesting in a practical setting presents a complex optimization challenge that demands further investigation. In addition, the authors in Ref. [17] provided an extensive review of the SWIPT scheme performance for cognitive radio NOMA (CR-NOMA), considering factors such as the type of the employed relay network, the number of relays, and the utilized communication protocol. As suggested, SWIPT was identified as a promising research area. The analysis may not adequately cover the complexities of deploying SWIPT in dynamic, real-mobile network conditions, where factors such as user mobility, varying signal quality, and environmental interferences play significant roles. Correspondingly, the authors in Ref. [18] developed a wireless power transfer (WPT) scheme to optimize time, power, and sub-channel allocation, aiming to maximize the EE OFDMA-based NOMA system. They proposed an iterative algorithm to obtain the sub-optimal solution to deliver the upper bound with guaranteed convergence. The resource allocation scheme demonstrated superior performance compared to the OFDMA. The iterative process's inherent complexity and time demands could constrain the scheme's efficiency [18] in dynamic or resource-limited network settings. Moreover, the pursuit of an upper-bound solution may not comprehensively address the practical limitations and diverse conditions prevalent in actual network deployments. On the other hand, resource allocation was divided into three sub-problems in Ref. [19], focusing on optimizing user matching, power allocation, and sensing duration to maximize the sum rate and energy harvesting for uplink NOMA. This approach was applied based on cognitive radio, OFDMA, and SWIPT. It aimed to improve the capacity and extend the lifetime of the green IoT while using power splitting (PS) mode for energy harvesting from the signals of the radio frequency (RF). Further, the work employed overlay and underlay modes in the cognitive OFDMA, and the proposed algorithm showed a balanced performance of the data rate with respect to the required energy. However, the challenge of balancing data rate performance with energy needs in diverse IoT environments highlights the need for additional refinement and practical testing of the algorithm to ensure its efficacy. In Ref. [20], a multi-user cluster scheme was proposed to maximize the SST in HetNet for downlink NOMA. Moreover, the $\epsilon$-optimal OAA was utilized to address the formulation of the proposed strategy problem. This approach employed a key performance indicator (KPI) to assess various aspects, including mobile user admission into the cluster, user association, fairness in association, and the overall sum-secrecy throughput. The proposed scheme outperformed the traditional OMA and the existing schemes in terms of KPI. Further, the adaptability of the strategy's performance in HetNet-NOMA with varied user's QoS and network conditions demands a more thorough evaluation to confirm its overall efficacy.

On the other hand, advanced stochastic optimization techniques were proposed in Ref. [21] to transform the resource allocation problem into a deterministic problem for task off-loading, focusing on delay constraints to minimize the energy consumption for NOMA-enabled IoT. The proposed scheme showed more effective performance than conventional schemes. Overall, transforming the resource allocation problem into a deterministic problem might overlook the inherent uncertainties and variability in real IoT environments. Although the scheme outperformed traditional methods, its applicability in diverse IoT scenarios with varying network conditions and user QoS demands requires further investigation. Cao and Zhao [22] divided joint resource allocation into sub-carrier allocation, power control, and time switching (TS) to maximize the user-centric energy efficiency in the IoT-NOMA system. Sub-carrier optimization was tackled using a two-sided matching algorithm due to the problem's mixed-integer non-linear programming (MINLP) nature. The successive convex approximation (SCA) was also proposed to solve fractional programming linked to user-centric energy efficiency. This approach showed better performance and convergence than OFDMA. Nevertheless, dividing the problem into three sub-problems may not effectively capture the full complexity and scalability challenges in diverse real-world IoT applications. In Ref. [23], a hybrid beamforming approach was proposed based on partially and fully connected hybrid beamforming to improve the capacity with minimal power consumption in the multi-antenna NOMA network. The suggested hybrid beamforming outperformed the various network models in terms of significant energy efficiency. However, the practical deployment of the proposed hybrid beamforming in real network environments faces challenges due to its complexity, particularly concerning hardware demands and advanced signal processing. This complexity could lead to increased energy consumption owing to the intensive computational processes and power dissipation across the multi-antenna system, potentially offsetting some of the efficiency gains. Furthermore, a resource allocation algorithm was proposed based on the Lyapunov optimization framework in Ref. [24] to maximize energy efficiency while adhering to minimum user's QoS and maximum transmit power constraints in the NOMA network. The optimization problem was divided into three sub-problems, two of which were linear problems, and the third problem was solved using the Lagrangian function. The authors also derived the control parameter under fixed queue stability, effectively balancing energy efficiency and delay while achieving significant energy efficiency improvement [24]. Despite the algorithm effectively achieved balanced energy efficiency and delay, its performance under varying network loads and conditions considering dynamic queue conditions, needs further exploration to confirm its efficacy in more diverse network scenarios. In Ref. [25], SCA was utilized to transform the power allocation into the sequence of convex problems, combined with greedy sub-carrier allocation as a resource allocation scheme to maximize energy efficiency in generalized frequency division multiplexing (GFDM) and NOMA. The proposed scheme demonstrated superior performance, with GFDM suggested for further investigation to improve the wireless communications. Besides, utilizing greedy methods for sub-carrier allocation could lead to sub-optimal solutions, especially in networks with high user density or diverse data demands. Srilatha et al. [26], developed a fair energy-efficient power allocation algorithm to achieve a balanced trade-off between energy efficiency and outage under imperfect channel state information (ICSI) in downlink NOMA. The proposed scheme demonstrated a significant improvement with a modest fairness index, outperforming the OFDMA. Admittedly, the algorithm's performance across diverse network environments and under various user data demands still needs thorough validation to confirm its wide-ranging utility, especially under ICSI in downlink NOMA. In Ref. [27], the authors proposed Dragon Levy-based Lion Cub Generation (DL-LCG) for resource allocation to achieve a balanced trade-off between energy efficiency and spectral efficiency while maintaining a minimum data rate for a hybrid multi-carrier NOMA system. This hybrid system incorporated OMA and NOMA, including various elements such as the total degree of freedom (DoF), user clustering, sub-carrier, power allocation, and multiple access mode selection. The proposed scheme was evaluated favourably in terms of cost analysis. Despite the scheme's promising cost analysis, the complexity of a hybrid system that merges OMA and NOMA could present considerable challenges to the algorithm's practicality and operational efficiency, especially in dynamic networks with differing user densities. Further, authors in Ref. [28] developed a joint resource allocation strategy aimed at maximizing the weighted sum of energy efficiency for the uplink within a multi-carrier relay network operating under the NOMA system. This joint resource allocation was designed as two sub-problems, using hospital-residents matching theory for sub-carrier assignment and an iterative solution procedure for power allocation across sub-carriers to address the non-convex optimization problem of the weighted-sum energy efficiency maximization. The proposed joint resource allocation demonstrated a comparable weighted sum energy efficiency while achieved a satisfied QoS with low complexity. Alternatively, the user scheduling and power allocation scheme were proposed to maximize the energy efficiency in millimetre wave NOMA (mm-NOMA) [29]. In this scheme, random beamforming was employed at the BS, focusing on user scheduling first and then the power allocation to reduce the feedback overhead. The proposed scheme showed improved energy efficiency compared to the conventional schemes. Moreover, prioritizing user scheduling before power allocation to reduce feedback overhead may not optimally address the unique propagation challenges and high sensitivity to blockages characteristic of mm-wave frequencies. In Ref. [30], the authors introduced proportional fairness constraint into the resource allocation scheme to maximize energy efficiency under perfect CSI for multiple-input-multiple-output (MIMO) NOMA. Two sub-problems were developed since energy efficiency is a non-convex optimization problem, utilizing the golden section search to determine the power allocation for fixed power and the fractional programming method to determine the total transmitting power. The MIMO-NOMA showed an acceptable performance with the introduced proportional fairness constraint, achieving decreased energy efficiency but improved fairness. Perfect CSI might not reflect the varying, unpredictable, and imperfect channel states in real network scenarios, potentially affecting the scheme's practicality. The resource allocation problem in Ref. [31] was decoupled into two sub-problems as sub-channel matching and power allocation. The SCA was employed to transform the problem into a convex one, reducing the computation complexity arising from the non-convexity of the energy efficiency maximization [31]. A super-modular game was introduced, and an algorithm was designed to converge to the Nash equilibrium point for power allocation. The proposed scheme achieved a sub-optimal solution for the NOMA system and demonstrated a superior energy efficiency performance than the OFDMA [31]. Nonetheless, the strategy of using Nash equilibrium for power allocation, while conceptually robust, might face practical challenges in the dynamic realities of real-mobile network environments, where network conditions and user demands are continuously changing. In Ref. [32], the authors proposed iterative water-filling (WF) for resource allocation to maximize the energy efficiency for uplink in multi-carrier NOMA, where users had access to the available sub-carriers. The maximization of the energy efficiency problem was transformed into a series of sub-problems focused on sum rate maximization sub-problems, relying on fractional programming and iterative WF. This approach highlighted the superiority of the NOMA over the OMA in terms of energy efficiency. The computational demands in processing of these iterative calculations could hinder its practical application, especially in scenarios with high user density, diverse user's QoS. Conversely, a weighted energy efficiency power allocation scheme was developed to maximize the throughput based on chained fog structure (CFS) in multi-carrier NOMA [33]. This scheme involved a user pairing and power allocation with less complexity. The proposed scheme achieved a 12.7 % increase in energy efficiency compared to the dynamic network resource allocation (DNRA) algorithm, and dynamic programming (DP) recursion [33]. While the notable 12.7 % enhancement in EE, anchored on the chained fog structure's stability and reliability, may not consistently translate to practical scenarios, especially considering the system's design based on uncorrelated signal assumptions. This factor could limit the applicability of the proposed solutions in varying and dynamic network environments. Adam et al. [1], developed a user scheduling and power allocation scheme to maximize the weighted sum energy efficiency in multi-carrier NOMA. The successive pseudo-convex approximation (SPCA) was applied to transform the weighted sum energy efficiency into a separable scalar problem, allowing for parallel problem-solving. Fractional programming, and Lagrange dual multiplier method were utilized for user scheduling. Constraints were relaxed using Dinkelbach's algorithm to characterize the closed-form power allocation, resulting in a superior energy efficiency performance better than the existing schemes [1]. Although the authors did not fully address the computational feasibility of their approach, as the third algorithm requires $O(MNKI)$ iterations. This computational demand is influenced by the separable nature of the approximate function and the iteration count for the sub-gradient operation. Additionally, the method used for calculating step size further affects the total number of iterations required, presenting a significant consideration for the scheme's practical implementation. An alternative method involved devising a strategy for channel assignment and power allocation, with the primary goal of maximizing energy efficiency. This approach took into account factors such as user fairness, minimum data rate requirements, and the constraints on maximum transmit power within the NOMA network [3]. This scheme employed the MOSEK function solver (cvx tool) for channel assignment and Dinkelbach's scheme using the fmincon function solver, maintaining the relevant constraints. The proposed scheme achieved significant energy efficiency gains over the traditional OMA scheme [3]. The proposed approach scalability across diverse user scenarios, and computational efficiency for real-time deployment require further in-depth analysis to ascertain its broader applicability. Furthermore, the advance complexity lies in the difficulty of achieving a global solution due to the non-convex nature of the problem.

### 1.3. Motivation and contribution

Direct numerical methods are often used for radio resource allocation in wireless communication. However, they may not be efficient for non-convex and NP optimization problems [34]. As the energy efficiency problem is inherently non-convex, transforming it into a solvable optimization problem is crucial for obtaining an effective solution [ [1–7,10–25,28–34]]. However, it's worth noting that transforming a non-convex optimization problem into sub-problems does not guarantee a tractable solution in all cases [30–34]. Typically, an approximate solution is addressed for problems converted from non-convex to convex, and it may not be optimal. Hence, numerical techniques are commonly employed to tackle individual sub-problems, like power allocation and user pairing, in order to obtain approximate optimal solutions for resource allocation to maximize EE within the NOMA system [30–34]. This pattern has been identified in prior studies where distinct methodologies were employed separately for user pairing and power allocation. Overall, an integrated approach should be utilized to concurrently optimize power allocation and user pairing, thereby achieving maximal energy efficiency through efficient resource allocation [34]. The non-convexity nature renders it difficult to solve the resource allocation problem using standard polynomial-time algorithms, posing a significant hurdle in achieving optimal and dynamic solutions in NOMA network. Consequently, metaheuristic algorithms represent one of the potential methods for dynamic and iterative optimization, particularly suited for solving non-convex optimization problems without altering the nature of the problem.

Simulated annealing is one such metaheuristics optimization algorithm that emulates the process of physical annealing. It aims to achieve the approximate global solution, similar to how a material is subjected to high temperatures and then gradually cooled to attain a crystalline state with minimal defects and energy. The annealing process starts with the melting phase, transitioning from a molten state to a stable crystalline state without defects [35,36]. SA algorithm is applied to minimize the objective function, allowing it to find the global solution, as opposed to stochastic local search algorithms. SA has the advantage of escaping local minimum traps and converging rapidly with sufficient iterations. Unlike the gradient descent algorithm, SA is a global optimization algorithm that does not rely on a specific assumption about the objective function [35–37].

Furthermore, SA is highly adaptable and effective for addressing both combinatorial and continuous optimization problems, regardless of whether the objective function exhibits convex or non-convex features. Hence, SA is proposed as a solution to the resource allocation problem for maximizing energy efficiency since the problem is addressed as a non-convex optimization problem in the NOMA system. In the NOMA system, multiple users coexist on the same channel, each having different power levels, particularly in the power domain. In such scenarios, finding optimal solutions becomes exceptionally critical [4]. Thus far, there has been no straightforward scheme reported for resource allocation optimization problems aiming to maximize energy efficiency in NOMA. The proposed SA scheme is utilized for optimizing both user pairing and power allocation, ultimately aimed at maximizing energy efficiency within the NOMA system. Moreover, SA is designed to tackle the resource allocation issue by establishing user and sub-channel assignments, assigning the necessary channel power, and distributing power among users who share the same channel. In this system design, differences in channel conditions are utilized for user pairing, employing two configurations: "hot" and "cold" configurations to achieve optimal matching [34]. This work introduced a novel standalone resource allocation algorithm, specifically developed to maximize energy efficiency in the downlink NOMA system for the 5G network.

### 1.4. Paper organization

The rest of the paper is structured as follows: Section 2 outlines the downlink NOMA system design and mathematical formulation. Section 3 offers an in-depth explanation of the proposed algorithm for resource allocation. Section 4 presents the system design model and analyses the results. Finally, the conclusion of this work is drawn in Section 6.

## 2. System model

In this system design, the BS is centrally positioned within the cell and a total number of $U$ users are distributed in a uniform distribution in a downlink single input single output (SISO) NOMA system. Within the NOMA system design, the BS is equipped with SC to multiplex multiple users and serve them simultaneously at the same frequency, code, and time utilizing the features of the NOMA-power domain. Multiplexing in the power domain represents the core multiplexing scheme for NOMA, allocating varying power levels to users who share the same channel. This is in contrast to OMA, which does not fully utilize the power domain [4,5]. The standard NOMA concept is illustrated in Fig. 1.

In this system, the total number of channels is denoted $N_{sc}$ and an equal bandwidth is allocated among the channels, calculated as $B_{sc} = B_{total} / N_{sc}$, where $\mathrm{B_{total}}$ represents the total available bandwidth. The channels are indexed as $\mathrm{n} \in \{1, 2, \ldots, \ldots, \mathrm{N_{sc}}\}$, each is assigned to the total number of users $U$ where $u \in \{1,2,.....,U\}$. For the sake of simplicity, only two users are multiplexed on the same channel for less complexity and the number of users multiplexed is *ith* user denoted as $U_{i,n}$ on the same *nth* channel where $U_n \in \{U_1, U_2, ...., U_{N_{sc}}\}$. To facilitate this multiplexing, the BS employs SC to combine the signal of the two users on the same channel before transmitting the superimposed signal. The BS then transmits this signal on the channel, targeting the intended users as follows [4]:

$$\mathrm{x_n} = \sum_{\mathrm{i=1}}^{\mathrm{U_n}} \sqrt{p_{\mathrm{i,n}}} \widehat{x}_i, \tag{1}$$

The superimposed transmitted signal is represented $x_n$ , where $\widehat{x}_i$ is the transmitted symbol for the *ith* user sharing the same channel *n*. The channel power for channel *n* is denoted $P_n$ and $p_{i,n}$ signifies the power allocated to *ith* user on this channel. The power constraints are defined as follows $\sum_{i=1}^{U_n} p_{i,n} = P_n$, and $p_{i,n} = 0$ when the user is not assigned to a particular channel. The received signal [4] at the *kth* user from channel *n* is formulated as follows:

$$Y_{k,n} = g_{k,n}\, x_n + N_{k,n} = \sqrt{p_{k,n}}\; g_{k,n}\, x_k + \sum_{i=1, i \neq k}^{U_n} \sqrt{p_{i,n}}\; g_{k,n}\; x_i + \mathbb{Z}_{k,n}, \tag{2}$$

The coefficient representing the channel between the user $U_{k,n}$ and the BS is denoted $g_{k,n}$ and defined as $g_{k,n} = h_{k,n} / P_{\ell}(d)$, where $P_{\ell}(d)$ is the path loss function accounting distance $(d)$ between the $U_{k,n}$ and BS, and $h_{k,n}$ represents Rayleigh fading channel gain. The term $\mathbb{Z}_{k,n}$ corresponds to Additive White Gaussian Noise (AWGN) and is represented as $\mathbb{Z}_{k,n} \sim CN(0, \sigma^2)$, where $\sigma^2$ represents variance with zero mean. The power spectral density is $N_\circ$ applied to estimate the variance as $\sigma^2 = (B_{total} / N_{sc}) N_\circ$. In a NOMA system, co-channel interference is a significant factor due to the transmission of superimposed signal messages to multiple users multiplexed on the same channel. To mitigate this interference, SIC is introduced in the NOMA system. However, without considering the SIC, the signal-to-interference-plus-noise ratio (SINR) received at *kth* user on *nth* channel can be expressed as follows [34]:

$$SINR_{k,n} = \frac{P_{k,n}\; g_{k,n}}{\sum\limits_{i=1, i \neq k}^{U_n} P_{i,n}\; g_{k,n} + \sigma_n^2} = \frac{P_{k,n}\; G_{k,n}}{\sum\limits_{i=1, i \neq k}^{U_n} P_{i,n} G_{k,n} + 1}, \tag{3}$$

The term $G_{k,n}$ represents the channel response normalized by noise (CRNN) for *kth* user on *nth* channel and is calculated as $G_{k,n} \triangleq |g_{k,n}|^2 / \sigma_n^2$ , where $\sigma_n^2$ represents the noise power on the channel and is defined as $\sigma_n^2 = E[|\mathbb{Z}_{k,n}|^2]$. The data rate function is formulated based on Shannon's capacity formula on the channel as given [34]:

$$R_n = B_{sc} \sum_{i=1}^{U_n} log_2 \left( 1 + \frac{P_{k,n} \left| G_{k,n} \right|^2}{1 + \sum\limits_{i=1, i \neq k}^{U_n} P_{i,n}\; G_{k,n}} \right) = B_{sc} \sum_{i=1}^{U_n} log_2 \left( 1 + SINR_{k,n} \right), \tag{4}$$

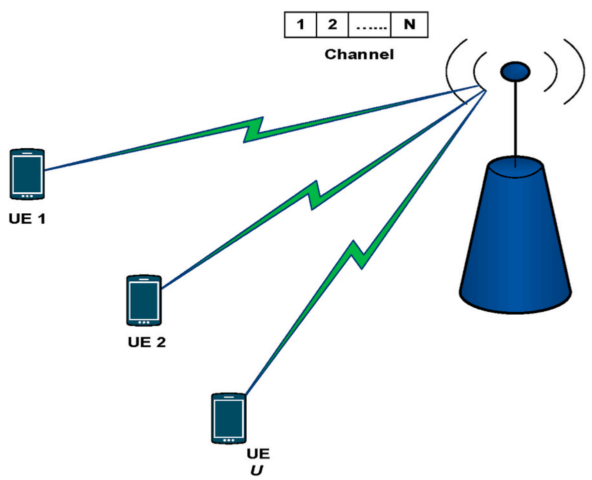


**Fig. 1.** NOMA standard model [4].

The SINR received at the user $U_{k,n}$ is expressed as follows [34]:

$$\gamma_{k,n} = \sum_{i=1, i\neq k}^{U_n} P_{i,n}\, G_{k,n}, \tag{5}$$

In the downlink NOMA system, the physical layer is responsible for performing modulation, encoding, and superimposing messages of the multiplexed users on the selected channel. Additionally, it assigns different power levels based on the multiplexing in the power domain. The BS employs a power allocation strategy that prioritizes the users with weak channel conditions by assigning more power to them and less power to good channel conditions, ensuring significant signal acknowledgement. The multiplexing scheme applied by the BS prioritizes users in descending order of channel gain to facilitate SIC performance at the receiver. Fig. 2 illustrates the structure of the NOMA system, with the BS acting as the transmitter and the mobile equipment (ME) serving as the receiver.

Alternatively, the SIC is conducted iteratively at the receiver side to successfully decode the superimposed message received at each user. This NOMA system design can be applied with the correlation of the SC, SIC, power allocation, and user pairing based on channel gain order. Thus, the good channel condition's users perform SIC according to the BS acknowledgement that can decode the combined signal and cancel it, then decode the intended signal. On the other hand, the user with the weak channel condition treats the unwanted signal as noise and then decodes the required signal.

Moreover, in NOMA, users with good channel condition, denoted as $U_{1,n}$ are multiplexed with the users having weak channel condition user like $U_{2,n}$ on the same channel $n$, where the channel gain $|G_{1,n}|^2 \geq |G_{2,n}|^{\,2}$. This multiplexing is carried out with allocating power, where $P_{1,n} \leq P_{2,n}$ [38–40]. A user with a good channel condition applies the SIC to decode the interference signal and subtract it, thereby successfully decoding the intended signal. In contrast, users with the weak channel condition treat the other signal as noise. For instance, users multiplexed based on channel order: $|G_{1,n}| \geq |G_{2,n}| \geq \ldots \geq |G_{k,n}| \geq |G_{k+1,n}| \geq \ldots \geq |G_{U_n,n}|$. This allows optimal SIC application, with user $UE_k$ having good channel conditions capable of decoding and subtracting the signals of $UE_{k+1}$.. $UE_{k+2}, \ldots, UE_{U_n}$ who have weak channel conditions, ensuring successful interference cancellation. Subsequently, user $UE_{k-1}$, who experiences a weak channel condition, can effectively eliminate interference from $UE_k$ by treating the interfering signal as noise, allowing for the successful decoding of the intended signal. Each user is acknowledged to decode the intended signal and able to treat the interference power using SIC and consider it as noise [4]. Furthermore, the SIC performance on $U_{k,n}$ is expressed as follows [34]:

$$SINR_{k,n}^{SIC} = \frac{P_{m,n}\, G_{k,n}}{1 + \sum_{i=1, i\neq k}^{k-1} P_{i,n} G_{k,n}}, \tag{6}$$

The effectiveness of SIC hinges on the allocation of more power to users with weaker channel conditions and less power to users with stronger conditions, guided by full BS acknowledgement. In the case of users with good channel condition user, the signal of the weak channel condition user will be decoded first due to the substantial power ratio. Subsequently, it is subtracted from the overall signal, enabling the successful decoding of the intended signal for users with good channel conditions. Conversely, users with weaker channel conditions experience a higher power level, effectively treating the power noise and signals from other users as mere noise. The allocation of power ratios among multiplexed users plays a pivotal role in achieving the optimal application of SIC, capitalizing on the diversity of power allocation levels and varying channel conditions.

## 3. Problem formulation

The resource allocation problem in this NOMA system is formulated with the goal of maximizing energy efficiency while minimizing energy consumption. In the context of mobile communication networks, this optimization scheme seeks to achieve the highest possible data rate with the least amount of energy consumed [40]. Energy efficiency is directly proportional to data rate and inversely

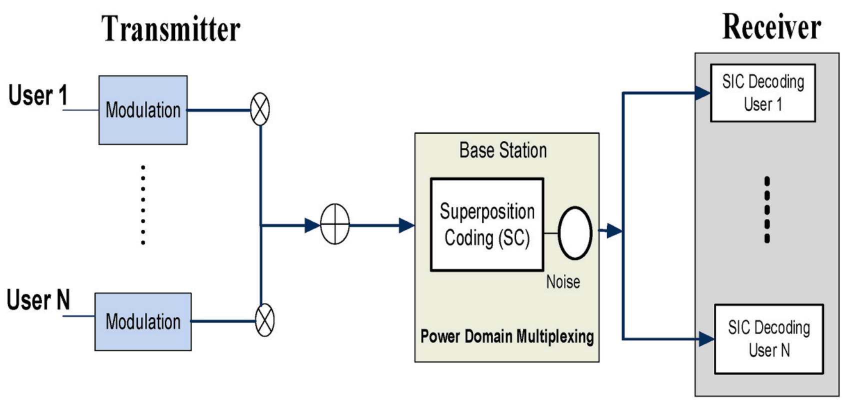


**Fig. 2.** NOMA communication system diagram with SC and SIC [ [4,34]].

proportional to energy consumption, representing the network's ability to provide substantial data rates while conserving energy [41, 42]. Therefore, data rate calculation serves as a standard metric for estimating energy efficiency, as per the capacity theorem, considering energy consumption within the network [42]. In this system, power is allocated to each channel as channel power $P_n$, and the data rate $R_n$ is defined for each channel $n$. Consequently, the total data rate is expressed as follows [34]:

$$R_{Total} = \sum_{n=1}^{N_{sc}} R_n, \tag{7}$$

User multiplexing in this system relies on the difference in channel conditions, where it is determined that $G_{1,n} \geq G_{2,n}$ on the same channel. This condition is incorporated into the optimization function as follows [34]:

$$f(P_n) = B_{sc1,n}\, log_2\left(1 + \delta_n P_n G_{1,n}\right) + B_{sc2,n}\, log_2\left(1 + \frac{(1-\delta_n) P_n G_{2,n}}{1 + \delta_n P_n G_{2,n}}\right), \tag{8}$$

The power allocation in this system, determined by the proportional power factor $\delta_n$, is crucial for users who share the same channel $n$. When a user has a strong channel condition, they can perform SIC, where the proportional factor $\delta_n$ takes values within the range $\delta_n \in (0,1)$. This optimal power allocation strategy is essential to allocate more power to users with weaker channel conditions, ensuring the effective implementation of SIC while considering appropriate user pairing. The proposed user pairing approach takes into account various user pairing scenarios based on differing channel conditions. The optimization of power allocation, user and channel assignment collectively forms a resource allocation problem aimed at maximizing energy efficiency within the NOMA system. In wireless communication, energy efficiency is defined as the maximum amount of transmitted data bits relative to unit energy. In the NOMA system, energy efficiency is influenced by both the transmit power for each channel, denoted as $P_n$, and the additional power consumption related to circuit power, denoted as $P_c$. The energy efficiency for each channel is expressed as follows [ [6,34]]:

$$E_n = \frac{R_n}{P_n + P_c}, \tag{9}$$

The overarching goal of this system is to maximize energy efficiency, and this is described as follows [ [6,34]]:

$$E_{Total} = \sum_{n=1}^{N_{sc}} \frac{R_n}{P_n + P_c} = \sum_{n=1}^{N_{sc}} E_n, \tag{10}$$

In this system, the resource allocation problem is formulated to maximize energy efficiency, and the objective function is presented hereunder [ [6,34]]:

$$\underset{P_n > 0}{Max} \sum_{n=1}^{N_{sc}} \sum_{k=1}^{U_n} \frac{R_{k,n}(P_{k,n})}{P_c + P_n} = \sum_{n=1}^{N_{sc}} \frac{R_n(P_n)}{P_c + P_n}, \tag{11}$$

*Subject to:*

$$\boldsymbol{C_1} : \sum_{n=1}^{N_{sc}} P_n \leq P_{Max}, \tag{12}$$

$$\boldsymbol{C_2} : \sum_{n=1}^{N_{sc}} R_{m,n}(P_n) \leq R_{Min}, \tag{13}$$

The objective function (11) aims to maximize energy efficiency while subject to constraints $C_1$ and $C_2$. The resource allocation problem encountered in this NOMA system is known to be non-convex and characterized as NP-hard. Energy efficiency, in this context, represents a trade-off between transmission capacity and power consumption, with the circuit power assumed to be 1 Watt [6]. Hence, in this system design, the resource allocation is treated as a single optimization problem, focusing on maximizing energy efficiency within the NOMA system.

## 4. Resource allocation problem

In this system design, SA is proposed as a solution to optimize resource allocation to enhance the energy efficiency of the downlink-NOMA system. The resource allocation problem is divided into several components, including channel power allocation, user and channel assignment, and power ratio among the multiplexed users on the same channel. The SA algorithm is applied to address these aspects by optimizing the channel power $P_n$ with respect to the maximum transmit power, match the users and channels with respect to the channel condition, and determine the power ratio $\delta_n$ for allocating the necessary power to each user sharing the same channel.

SA, in essence, is a metaheuristic algorithm inspired by the physical annealing process commonly used in the metallurgical [35–37]. Physical annealing involves subjecting a solid material to high temperatures and then slowly cooling it down to achieve a crystalline structure with minimal defects and energy usage. During the high-temperature phase, the atoms within the material gain sufficient energy to move and rearrange themselves, resulting in a high-energy state. As the material cools down, the energy levels decrease, eventually leading to the formation of a stable crystalline structure with minimal energy. Thus, the primary goal of the proposed algorithm is to maximize energy efficiency as a cost function similar to physical annealing using the energy function as the optimization function. SA operates as a straightforward optimization algorithm that can effectively escape local optimal by using a set of control parameters [35–37]. These control parameters can be defined based on the problem design such as initial temperature, cooling schedule, and algorithm termination as an empirical basis that can be tuned to obtain maximum performance. SA is a probabilistic optimization method that lacks memory, aiding in escaping local minimal but potentially leading to inefficiencies and slower convergence in complex scenarios due to its reliance on cooling schedule settings and sensitivity of the parameters. SA is known for its ability to accept both better and worse solutions with certain probabilities, making it a versatile optimization approach [35–37].

In the SA design, $a_n$ represents a fraction of the maximum transmit power, denoted as $P_{Max}$ and is defined as $a_n = P_n / P_{Max}$. Similarly, the power ratio $\delta_n$ is a fraction of the power allocated to each user multiplexed on the same channel. User and channel assignment is carried out based on the channel gain difference. These three parameters within the objective function are instrumental in obtaining a solution, where any variations in their values represent potential solutions until the optimal one is achieved.

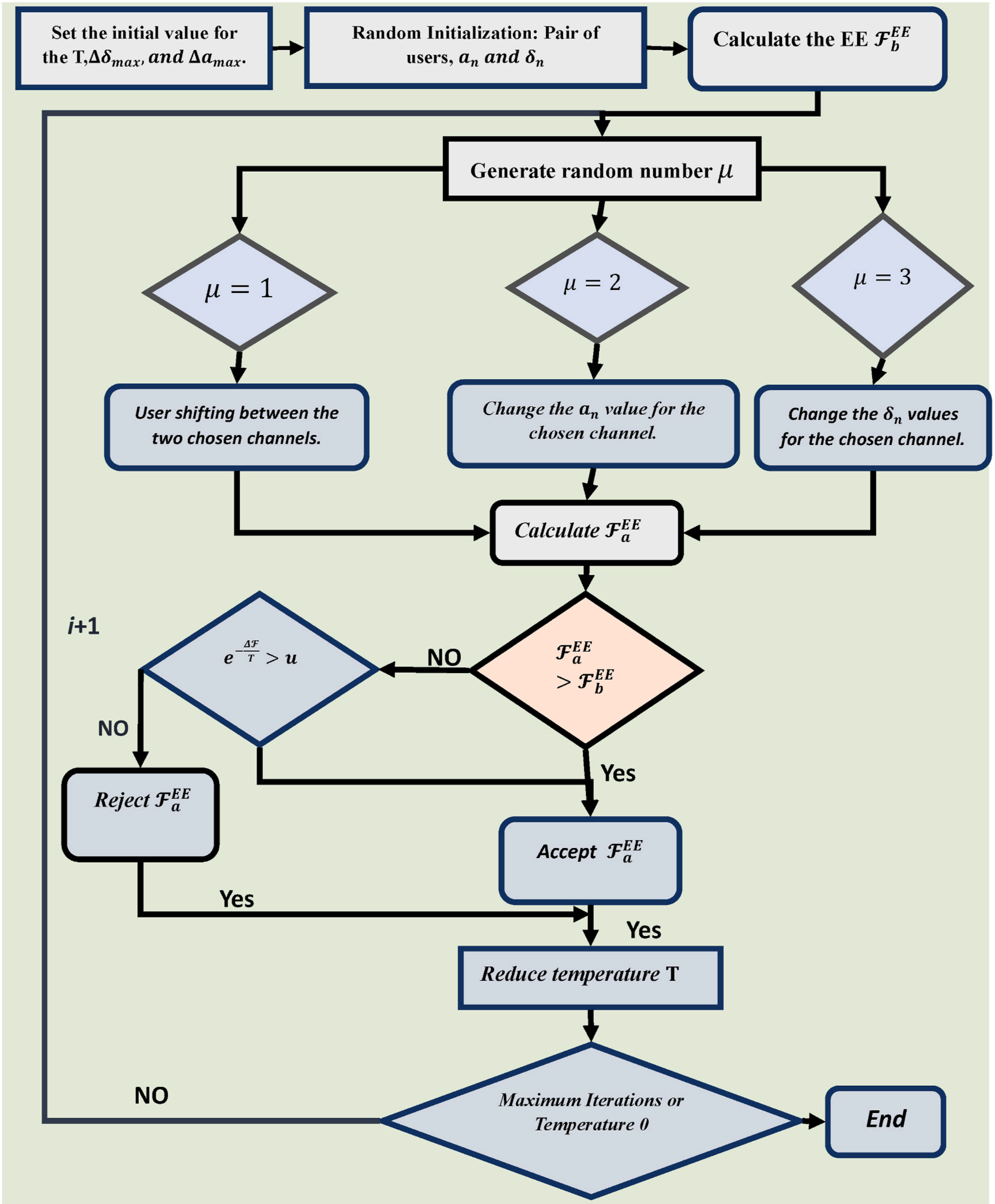


**Fig. 3.** Proposed Scheme Flowchart [34].

Furthermore, the SA algorithm commences with an initial random solution, which is defined as the current best solution. This is done by assigning a random value of $a_n$ to estimate the channel power, assigning a random value $\delta_n$ as power ratio, and randomly multiplex two users on the same channel based on the channel gain order established as the current best solution. This initial solution serves as the baseline within the objective function. Subsequently, various parameters are adjusted, and the cost function is evaluated to compare the new solution with the initial current best solution. The optimization system mode determines the modification of one parameter. Consequently, the algorithm accepts the new solution if it proves superior to the initial current best solution. Otherwise, it computes the probability using the Boltzmann distribution, specifically $e^{-\frac{\Delta\mathscr{F}}{T}}$, where $\Delta\mathscr{F} = \mathscr{F}_b^{EE} - \mathscr{F}_a^{EE}$. A random variable $\varepsilon$ is generated between 0 and 1, and the solution is applied only if $\varepsilon < e^{-\frac{\Delta\mathscr{F}}{T}}$. After this phase, the temperature decreases, marking the commencement of a new iteration for the refined solution within the objective function. The resource allocation scheme, developed by the proposed SA algorithm is elaborated in Fig. 3.

The Energy efficiency is estimated whenever a single parameter is altered, with the other parameters are fixed in every iteration. This approach improves the time efficiency of resource allocation by continuously computing the EE function, varying only one variable per iteration while keeping others fixed. This significantly reduces the time complexity by avoiding complete recomputation of all variables in the EE objective function each time. In each iteration, only one parameter is modified, significantly reducing computational time and aiding in the decoupling of the resource allocation problem. This decoupling is crucial due to the inherent coupling of the resource allocation problem in the NOMA system, as illustrated in Fig. 3. The choice of which parameter to change in each iteration is determined by the system mode, where $\mu$ can take on values from the set $\mu = \{1,2,3\}$. When $\mu = 1$, changes are made to user and channel assignment while keeping the $a_n$ and $\delta_n$ values fixed. When $\mu = 2$, the channel power $a_n$ is changed while keeping the $\delta_n$ values and the current user pairing is unchanged. Finally, when $\mu = 3$, the proportional power ratio $\delta_n$ is modified while maintaining $a_n$ values and the current user pairing. The proposed SA algorithm is an automated and efficient scheme designed to ensure an optimal solution for resource allocation in the context of the coupled problem involving power allocation and assignment of users and channels. The objective function is formulated with a negative sign because the SA algorithm is a minimization algorithm. The subsequent sub-section outlines the proposed resource allocation scheme, which is divided into three concurrent sub-problems based on the SA algorithm [34].

### *4.1. User and channel assignment*

In the SA algorithm, the user and channel assignments are addressed during iterations when the system mode $\mu = 1$. The initial solutions for user and channel assignments are devised in two configurations: the hot configuration and the cold configuration, taking into account differences in channel gains. In this system design, users have access to all available channels to simplify the pairing scheme and account for the impact of channel gain differences effectively [43]. This approach ensures that even users with weak channel conditions achieve a minimum data rate with minimal power consumption, given the proper exploitation of channel gain differences. The initial design in the hot configuration randomly multiplexes a high channel gain users with poor channel gain users on the same channel and sets the solution as the current best solution. Conversely, in the cold configuration, the search begins with a good solution since both multiplexed users have good channel gains [43]. In the cold configuration, the channel and user exchanges are formulated based on the average channel gain ($Av_g$), calculated as follows [34]:

$$Av_g = \frac{\sum_{i=1}^{U} G_{i,n}}{U}, \tag{14}$$

where $G_{i,n}$ is the channel gain of the users sharing the same channel and $U$ is the total number of users. In the SA algorithm, the initial user and channel assignment is set in both configurations, taking into consideration the optimality of the SIC application. The average channel gain is also set as the channel gain threshold. This configuration considers channel gain differences to enhance energy efficiency maximization. The threshold of channel gain is applied in both the hot and cold configurations to ensure practical user and channel assignments. The initial user and channel assignment solution acts as the current best solution for the specific configuration of the objective function. The user and channel exchange step is then executed to generate a potentially better solution. In this step, two channels are randomly selected, and a comparison of the users on those channels is made based on their channel gains. Users with either high or low channel gains may exchange channels.

Subsequently, the EE objective function is evaluated with the new user and channel assignment. If the new solution proves superior to the current best solution, it is accepted and subsequently updated as the current best solution. Then, the temperature is lowered for the ongoing iteration, and the latest best current solution is recorded. In the hot configuration, the assignment is made without considering the channel gain threshold, resulting in high channel gain users being assigned with low channel gain users on the same channel. In the cold configuration, the high channel gain user is assigned to the same channel as the user whose channel gain falls below the channel gain threshold will be selected in the cold configuration as $G_{i,n} \le Av_g$. This assignment tests all possible user and channel assignment solutions involved in EE maximization.

### *4.2. Channel power allocation $P_n$*

The SA algorithm selects system mode $\mu = 2$ to determine the optimal channel power concerning the maximum transmit power as defined by $a_n$, a fraction of the maximum transmit power to allocate the required power for each channel. Allocating the necessary power for each channel in this manner, with $a_n = P_n/P_{Max}$, serves to minimize power consumption while potentially increasing energy efficiency. Changes in the channel power, represented by $P_n$, are influenced by the fraction $a_n$ in relation to the fixed variable of the maximum transmit power, $P_{Max}$. The formulation for the fraction power $a_n$ is as follows [34]:

$$\sum_{n=1}^{N_{sc}} P_n = \sum_{n=1}^{N_{sc}} a_n \times P_{max} = P_{max}, \tag{15}$$

$$\sum_{n=1}^{N_{sc}} a_n < 1, \tag{16}$$

In the initial system design, the value of $a_n$ is randomly assigned within the range $0 \leq a_n < 1$ to determine the channel power, $P_n$, for the objective function, and this value is stored as the current best solution. Following this, the SA algorithm adjusts the value of $a_n$ to alter the channel power $P_n$, for the chosen channel during the selected iteration, while recording the new best solution. This modification of $a_n$ occurs while keeping the current user and channel assignment, as well as the value of the power ratio, $\delta_n$, fixed. The SA algorithm evaluates the objective function and updates the new best current solution after modifying the channel power, $P_n$, provided that the new solution is superior to the previous current best solution. The set of the current best solutions is then updated with the newly accepted best current solution, and the current iteration proceeds with a reduction in the algorithm's temperature. Furthermore, the system design considers equal channel power allocation when the value of $a_n$ is fixed for all channels in relation to the maximum transmit power. To introduce variability, $a_n$ is changed while the other parameters remain constant, specifically by employing the formula $a_n = a_n + \rho\ \Delta a_{max}$, where $\rho$ is a random number ranging [-1,1]. This equal channel power allocation is implemented to assess the optimality of power allocation for enhancing energy efficiency in the NOMA system, based on mathematical derivations for data rates in NOMA [34].

### 4.3. *Proportional power ratio allocation* $\delta_n$

In this system design, only two users share the same channel $n$, specifically defined as $U_{1,n}$ and $U_{2,n}$. The difference in channel gain is defined as $G_{1,n} > G_{2,n}$, with channel power $P_n$ and power ratio $\delta_n$. The proportional power ratio $\delta_n$ is modified when system mode $\mu = 3$, where its value varies between 0 and 1 ($0 < \delta_n < 1$) to distribute the channel power among the multiplexed users on the same channel. Following the NOMA concept, more power is allocated to $U_{1,n}$ as the first user with a high channel gain, while less power is assigned to $U_{2,n}$ with a lower channel gain. This power allocation scheme in NOMA aligns with the SIC principle to mitigate interference. The power ratio $\delta_n$ is formulated in the objective function to assign the weaker channel condition user with more power and sufficient power to the better channel condition user, facilitating the application of SIC. Specifically, the power ratio value is small for the good channel condition user, $U_{1,n}$, whereas a larger power ratio is assigned to the user with a weaker channel condition, $U_{2,n}$. This configuration allows the good channel user, $U_{1,n}$, to decode and cancel the interference from the weaker channel condition users, as the power allocated to $U_{1,n}$ is sufficient for this purpose. Subsequently, the weaker channel condition user, $U_{2,n}$, treats the interference from the good channel user as normal AWGN noise, given the lower power allocation for $U_{1,n}$.

The power ratio $\delta_n$, is employed to balance the power allocation between the two users who share the same channel, ultimately maximizing energy efficiency. Therefore, the SA algorithm is proposed to determine the optimal value of value of the factor $\delta_n$ to maximize the EE objective function, subject to the constraint $\delta_n \in (0,1)$.The initial solution for the objective function starts with a randomly assigned value for the proportional power ratio $\delta_n$, which is preserved as the current best solution. This value is then modified based on the system mode. In system mode 3, one channel is randomly selected to alter the proportional power ratio $\delta_n$, and evaluate the objective function. If the new solution proves to be superior to the current best solution, it is embraced as the updated current best solution. This accepted new solution is then reflected as the current best solution, and the temperature for the current iteration is lowered. The proposed SA algorithm seeks to determine the optimal value for the power ratio, which varies between 0 and 1, to evaluate the EE objective function. The change in $\delta_n$, while keeping the other parameters constant, is expressed as $\delta_n = \delta_n + \rho\ \Delta\delta_{max}$, where $\rho$ is a random number ranging $[-1,1]$.

Moreover, the proportional power ratio, $\delta_n$, can take on different values for different channels, as channel power is also a variable optimized to maximize EE in NOMA. Thus, the value of the proportional power ratio, $\delta_n$, may vary according to the channel conditions of the multiplexed users, with EE serving as the criterion for determining the value with respect to the SIC application (see Table 1).

## 5. Results and performance analysis

The simulation results have been presented and analysed to evaluate the performance of the proposed algorithm. In this downlink NOMA system design, a single BS is situated at the center of a cell with a radius of 500 m, accommodating a minimum of 10 to a maximum of 60 users for algorithm validation. Users are uniformly distributed, ensuring a minimum distance of 50 m between each user and the base station, as well as a minimum distance of 40 m between users. The dedicated bandwidth for this system is 5 MHz, which is evenly distributed among the channels. Furthermore, to reduce SIC complexity, only two users are multiplexed on the same channel. Each user is assigned to one channel in the case of OFDMA while considering a decay factor of 0.4, as applied in FTPA [44]. The proposed algorithm has been implemented, developed, and assessed using MATLAB, with the system's parameters elaborated in Table 2.

The SA algorithm is employed to optimize resource allocation and is fine-tuned using specific model parameters as tabulated in

Table 3. These parameters include initial settings, initial temperature, perturbation mechanism, cooling schedule, and termination criteria, all aimed at maximizing the cost function efficiently.

The SA algorithm initiates with a high initial temperature, set as $T_{initial} = 100^{\circ}C$. Subsequently, a cooling schedule is applied to gradually decrease the temperature based on the following expression [35]:

$$T_i = T_{i-1} - \alpha\, T_{i-1}, \tag{17}$$

where $T_{i-1}$ represents the previous temperature value, and $\alpha$ is the variation coefficient. Setting $\alpha = 2/3$ ensures a gradual cooling schedule, which aids in escaping the local optimal and reaching the optimal solution effectively [35]. The proposed SA algorithm involves evaluating the objective function for a minimum of 2000 iterations, even for systems with the smallest number of users.

Fig. 4 illustrates the proposed scheme's impact on energy efficiency concerning a maximum transmit power of 12 W in a NOMA system with 10 users. The proposed SA algorithm with four scenarios improves the EE and exhibits overlapping trends with slight differences between the scenarios. The proposed solution demonstrates enhanced energy efficiency compared to the numerical schemes such as DC [6] and FTPA [44] schemes as well as OFDMA. Specifically, the proposed SA algorithm outperforms DC by 22 %, surpasses OFDMA by 47 %, and exceeds FTPA by 46 % [44]. Notably, the proposed SA scheme exhibits a gradual increase in energy efficiency with the augmentation of the transmit power. However, minimum energy efficiency is observed for the low transmit power, attributed to the full utilization of the maximum BS power. Ultimately, the proposed SA approach outshines the other schemes, although, at a certain point, energy efficiency experiences a decline, reaching the lowest values encountered in DC, OFDMA, and FTPA.

Fig. 5 presents how energy efficiency changes with an increasing number of users while keeping the maximum transmit power constant. The results clearly demonstrate that the proposed SA achieves superior performance of energy efficiency compared to the DC, FTPA, and OFDMA. The proposed scheme exhibits a consistent improvement in energy efficiency as the number of users increases, which stands in contrast to the trends observed for DC, FTPA, and OFDMA, where energy efficiency is notably lower for a system with 10 users. All four SA scenarios display similar performance across different user counts, resulting in overlapping solutions. Consequently, the proposed SA algorithm proves capable of providing high capacity even with a lower number of users while still enhancing capacity for a larger user count, effectively balancing this with energy consumption considerations. In particular, for a system with 20 users, the proposed SA algorithm achieves an energy efficiency 24 % higher than DC, 46 % higher than OFDMA, and 47.5 % higher than FTPA. This emphasizes the significant advantages of the SA algorithm in enhancing energy efficiency as the number of users grows.

Fig. 6 provides an insightful analysis of the proposed scheme's energy efficiency concerning the circuit power to BS power ratio $(P_c\,/P_{Max})$ while maintaining a fixed BS transmit power of 12 Watts. The results highlight the superiority of the proposed scheme in terms of energy efficiency, particularly for lower circuit power to BS power ratios. However, it is worth noting that, energy efficiency decreases as the $(P_c\,/P_{Max})$ ratio increases. Even with increasing $(P_c\,/P_{Max})$ ratios, the proposed scheme continues to achieve higher energy efficiency compared to DC, FTPA, and OFDMA, with a notable advantage of 35 % over the DC [6] and 55 % over the OFDMA in terms of power consumption. This emphasizes the effectiveness of the proposed scheme in maintaining a satisfactory level of energy efficiency even as the circuit power increases. The observed decrease in energy efficiency with rising circuit power $(P_c\,/P_{Max})$ is consistent with the definition of energy efficiency, where higher circuit power contributes to reduced energy efficiency. High circuit power, often attributed to factors like RF components, hardware equipment, and amplifier efficiency, can indeed lead to lower energy efficiency. Balancing the need for high data capacity with acceptable energy consumption poses a significant challenge in achieving an energy-efficient network. However, the NOMA system, particularly when employing the proposed standalone algorithm for resource allocation, demonstrates superior performance compared to DC, FTPA, and OFDMA in maximizing energy efficiency while considering circuit power constraints.

**Table 1**
Existing work Summary.

| Ref. | Objective | Proposed Algorithm |
|---|---|---|
| [2] | Maximize the EE downlink in the NOMA network. | The CPLEX optimization tool was applied to solve the LP. |
| [8] | Maximize the EE in the MC-NOMA system. | Matching algorithm and Dinkelbach's algorithm. |
| [9] | Improve the EE in the downlink NOMA system. | A numerical scheme for power allocation. |
| [10] | Maximize the EE in multi-carrier cognitive radio NOMA (MC-CR-NOMA). | Dinkelbach's for resource allocation scheme. |
| [11] | Maximize EE and fairness in downlink multi-carrier MC-NOMA. | Fractional programming with sequential optimization to solve power allocation and a greedy algorithm for sub-carrier allocation. |
| [13] | EE maximization in uplink multi-user NOMA. | Deep reinforcement learning (DRL) for power allocation. |
| [14] | Maximize the EE for multi-user and multi-cluster NOMA networks. | Stackelberg game competition for power allocation scheme and user clustering. |
| [15] | Maximize the EE based on machine-to-machine (M2M) communication in NOMA (M2M-NOMA). | Improved Rider optimization technique for resource allocation in M2M communication. |
| [20] | Maximize the sum-secrecy throughput (SST) for downlink NOMA in a heterogeneous network (HetNet). | $\epsilon$-optimal outer approximation algorithm (OAA) for clustering, user association, fairness association, and the SST. |
| [21] | Minimize the energy consumption for NOMA-enabled Internet of Things (IoT). | Transformation of the resource allocation problem into a deterministic problem using advanced stochastic optimization. Techniques. |
| [24] | Trade-off EE and delay under minimum user quality of service (QoS) and maximum transmit power NOMA network. | Lyapunov optimization and Lagrangian function for resource allocation. |

**Table 2**
System design Parameters.

| PARAMETERS | VALUE |
|---|---|
| **Bandwidth** | 5 MHz |
| **Number of Sub-channel s** | 128 |
| **Cell Radius** | 500 m |
| **Number of Base stations** | One |
| **Total Number of Users** | 60 |
| **Minimum distance between User – User** | 40 m |
| **Minimum distance between User – BS** | 50 m |
| **Maximum Transmit Power** | 12 Watt |
| **Circuit Power** | 1 Watt |
| **Maximum Number of Multiplexed users/channels** | 2 users |
| **Noise Power Spectral Density** | −174 dBm/Hz |
| **Shadow Standard Deviation** | 8 dBm |
| **Noise Figure** | 9 dBm |

**Table 3**
SA parameters.

| MODEL PARAMETERS | VALUE |
|---|---|
| **Initial Temperature** | $100^{\circ}C$ |
| **Variation Coefficient** | 2/3 |
| **Random Variable** | [-1,1] |
| **Boltzmann distribution variable** | [0,1] |
| **System mode** | $\{1, 2, 3\}$ |
| **Minimum Iterations** | 2000 |

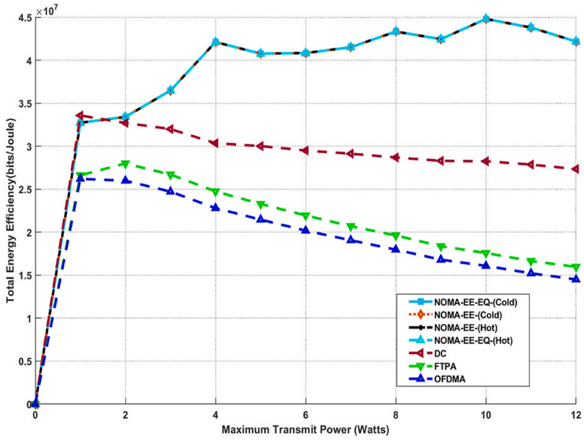


**Fig. 4.** Energy efficiency versus maximum transmit power for system with 10 users.

## 6. Conclusion

In this work, the resource allocation problem has been addressed by employing Simulated Annealing with the aim of maximizing energy efficiency in the downlink NOMA system. SA is implemented as a standalone scheme, addressing tasks such as user and channel assignment, channel power allocation, and power ratio allocation. The channel gain difference is employed in the user pairing with two configurations to ensure the optimal solution. Additionally, the maximum transmit power fraction has been utilized to accurately determine the required channel power relative to the maximum transmit power. Moreover, the proportional power ratios have been investigated to distribute the necessary power to the users multiplexed on the same channel. As a result, the SA scheme has managed to achieve an impressive 22 % improvement in energy efficiency compared to DC, 46 % compared to FTPA, and 47 % compared to OFDMA, all while maintaining a lower time complexity. It boasts a significant advantage, with a 35 % improvement over DC and a remarkable 55 % enhancement over OFDMA in terms of power consumption. These findings indicate that SA presents a viable and efficient solution for addressing the resource allocation challenge in the context of maximizing energy efficiency within NOMA systems in 5G networks. Future research should focus on enhancing the SA algorithm's scalability in larger, more complex networks, including its application in uplink NOMA systems and integration with IoT and massive Machine-Type Communication (mMTC) devices. Additionally, incorporating machine learning to refine SA could provide adaptive solutions for evolving network conditions and user

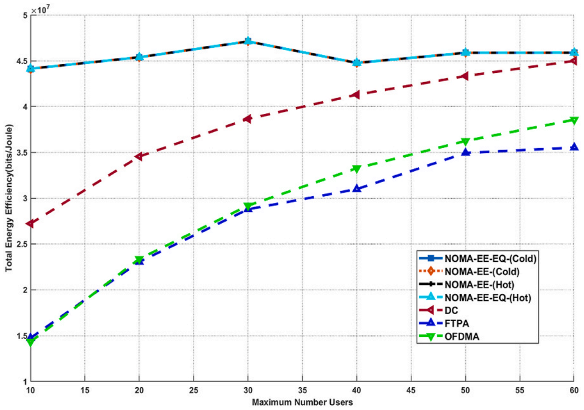


**Fig. 5.** Energy Efficiency Versus Different Number of Users for System with Maximum Transmit power 12 Watt.

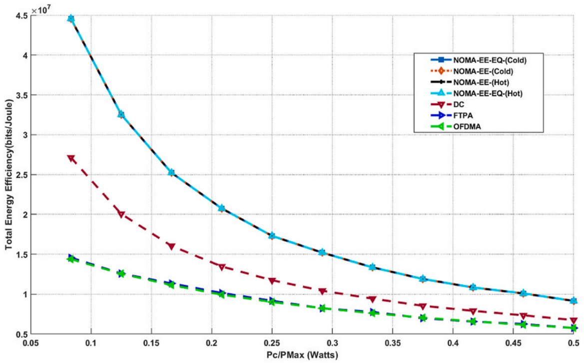


**Fig. 6.** Energy efficiency versus (Pc/Pmax) power for system with 10 users.

QoS, potentially making it a crucial tool for NOMA resource allocation in the 5G network.

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## Data availability statement

The authors do not have permission to share data.

## CRediT authorship contribution statement

**Osama Abuajwa:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sufian Mitani:** Writing – review & editing, Visualization, Supervision, Resources, Project administration, Investigation, Data curation, Conceptualization.

## Declaration of competing interest

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

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