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Efficient Power Allocation Algorithm in 5G Heterogeneous Networks Using an Improved Stackelberg Game Theory-Based Approach

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ABSTRACT

A major challenge in the Fifth Generation (5G) millimeter-wave networks is the high-power consumption resulting from the high density of installed base stations (BSs). To improve energy efficiency and optimize interference pricing, this research proposes an enhanced Stackelberg game theory (SGT) approach for effective power allocation in 5G heterogeneous networks. The enhanced SGT incorporates Hamilton–Jacobi–Bellman (HJB) equations to increase solution diversity and convergence compared with conventional SGT approaches. Furthermore, it introduces an Empowerment of Weak Player's Strategy (EWPS) mechanism to improve the search space and the balance between exploration and exploitation compared to the traditional SGT, thereby improving optimal power allocation in 5G networks. The radio network controller (RNC) acts as the leader and the BSs as the followers within the Stackelberg game structure. Using the non-cooperative game theory, the RNC determines the interference pricing for the third-layer BSs and users, who subsequently adjust their transmit power according to the specified interference price. The proposed SGT-HJB-EWPS scheme achieves efficient power allocation and pricing while improving convergence performance, reducing interference, and enhancing system capacity.

1. INTRODUCTION

The explosion of data-centric applications has placed modern communication systems under increasing pressure, with escalating demands for greater bandwidth, faster speeds, and minimal latency [1]. Applications such as real-time high-definition video streaming and the seamless operation of autonomous vehicles highlight the critical need for advanced, high-performance network infrastructures. The rollout of the Fifth Generation (5G)—and its successors—signifies more than just a technical upgrade; it introduces a paradigm shift in how connectivity is experienced and delivered [2].

A cornerstone of these next-generation mobile networks is the utilization of millimeter-wave (mmWave) bands, spanning frequencies from 24 GHz up to 300 GHz. Additionally, the architecture of 5G emphasizes heterogeneity, blending multiple access technologies and accommodating a wide array of user devices. This heterogeneous integration unifies various wireless standards, such as 4G, Long-Term Evolution (LTE), and Wi-Fi, into a cohesive, scalable system, enabling broader coverage and network capacity that far surpasses what traditional macro-cell deployments can support [3].

To meet coverage and capacity requirements, deploying smaller base stations (BSs) becomes essential. These small BSs help bridge coverage gaps while supporting higher user density. Furthermore, cooperative spectrum sharing between macro and small BSs optimizes network utilization. Despite these advancements, challenges persist—particularly in managing interference and allocating resources effectively, especially in scenarios where multiple data streams compete for limited bandwidth across overlapping channels or distinct nodes [4].

These frequencies offer vast bandwidth and ultra-high data rates, supporting the growth of advanced technological ecosystems such as the Internet of Things (IoT), augmented reality (AR), and smart cities. However, mmWave signals are susceptible to physical obstructions and have limited propagation range, necessitating dense BS infrastructure. This densification significantly increases the network's overall energy consumption. Although individual BSs consume moderate power, their cumulative energy usage across dense deployments becomes substantial. As demand for mmWave-enabled 5G networks rises, so does the energy consumption of the broader information and communication technology (ICT) sector. Telecommunication networks, as the backbone of the digital ecosystem, consume a significant share of this energy [5-7]. This surge in energy consumption raises environmental and economic concerns. Power-intensive communication infrastructure significantly contributes to global carbon emissions, prompting scrutiny amid growing demand for sustainable, eco-friendly solutions. Thus, reducing energy consumption is not only a matter of operational efficiency but also a commitment to environmental stewardship. Reports indicate that the ICT sector accounts for approximately 4% of global electricity use, with BSs responsible for 80–90% of this total. Dense network deployments also complicate user association. Efficient allocation of users to the appropriate BSs is essential for maintaining high-quality service and optimal network performance. Suboptimal user association can lead to network congestion, unbalanced load distribution, and reduced data rates [8, 9]. Therefore, addressing energy efficiency and user association simultaneously becomes critical under dynamic network conditions. To fully realize the potential of 5G mmWave networks, researchers must adopt integrated strategies that reduce power consumption while optimizing user association. Dynamic BS management plays a vital role in achieving this objective. Since user demand and traffic load vary over time and space, continuously operating all BSs results in resource inefficiency and excessive energy consumption. A more effective approach involves dynamically switching between BSs on or off based on real-time network conditions [10, 11].

5G heterogeneous networks employ three primary power allocation strategies: centralized, distributed, and semi-distributed. Centralized power allocation relies on a control center to gather channel, power, and signal-to-noise information and then distribute communication resources accordingly. While this method can optimize network performance, it requires complex infrastructure and significant processing overhead, complicating real-time implementation. In contrast, distributed power allocation eliminates the need for a centralized control unit. Each terminal independently allocates transmission power based on its own needs without exchanging information with others, resulting in a simpler and more scalable system. Semi-distributed power allocation strikes a balance between the two approaches. After the central controller performs initial resource distribution, individual BSs manage power allocation within their respective domains, combining the strengths of centralized coordination and localized decision-making [4, 9, 12, 13].

Various game-theory models have shown a notable improvement in power allocation performance, enhancing the quality of service (QoS) in 5G. Chen et al. [14] presented the traditional Stackelberg game theory (SGT)-based model for power allocation in 5G. However, the effectiveness of the SGT is limited by a rigid leader-follower structure, slower convergence, poor solution diversity, sensitivity to initial conditions, and an unbalanced exploration-exploitation balance. This study presents an improved SGT that uses Hamilton–Jacobi–Bellman (HJB) to enhance solution diversity and convergence in traditional SGT. It further uses the Empowerment of Weak Player's Strategy (EWPS) for enhancing the exploration-exploitation balance and the search space for optimal power allocation in 5G networks.

The remaining paper is structured as follows: Section 2 provides details on related work on game-theoretic power and resource allocation in 5G networks. Section 3 offers information regarding the proposed power allocation strategy. Section 4 discusses the simulation results. Section 5 delivers the conclusions and future scope of the work.

2. RELATED WORK

A vast growth in communication technology has led to a significant increase in mobile users and data traffic. Numerous methods and algorithms have been developed to address various problems in communication technology. The game theory approach is widely used due to its reliability and robustness in routing design, spectrum allocation, power allocation, and resource allocation. Power allocation is crucial in 5G technology. Various game-theoretic strategies, such as noncooperative games (NCGs), coalition games, and Stackelberg games, have been widely adopted for power allocation in 5G [3-5].

NCG theory does not consider consensus between players. The players individually make the strategic plan at the beginning and focus on boosting their interest. It assumes no collaboration or binding agreements between players. Each player considers others' strategies when choosing their own. The key solution concept is Nash Equilibrium, in which no player can benefit from unilaterally changing their strategy. The Nash Equilibrium theory plays a pivotal role in diverse fields, including economics, political science, and cybersecurity applications [6-9]. Shi et al. [10] addressed power allocation in distributed multiple-radar systems operating within a shared spectrum. Using NCG theory, they devised schemes that improve detection capabilities without disrupting coexisting systems. Building on this, Wang et al. [11] proposed a decentralized power control mechanism suitable for ultra-dense networks, a vital requirement for scalable and interference-aware 5G and beyond infrastructures. To enhance autonomy, Nguyen et al. [12] incorporated multi-agent deep reinforcement learning within an NCG framework for device-to-device (D2D) communications. This method allows devices to learn optimal power strategies without global network oversight, boosting energy efficiency and adaptability. Meanwhile, Fu and Su [13] introduced dynamic pricing into non-cooperative power games to influence user behavior. Their approach helps achieve more efficient equilibria by embedding economic incentives, which is particularly useful in smart grid and communication pricing systems.

Expanding the use of game theory beyond the communication layer, Zhang and Zhou [15] applied NCG models to cloud computing for task scheduling and resource management. Their algorithms strike a balance between computational loads and user autonomy, a crucial factor in distributed cloud environments. In two-tier femtocell networks, Liu et al. [16] used robust game-theoretic models to address power control between macrocell and femtocell users, ensuring reliable performance even in the presence of system uncertainties. Although not solely based on NCG, Zhou et al. [17] investigated distributed decision-making in Wireless Local Area Network (WLAN)-based indoor localization. Their anonymous crowdsourcing-based approach provides privacy-preserving and reliable location estimation in Global Positioning System (GPS)-denied environments, aligning well with the broader goal of decentralized optimization. Lastly, Surender et al. [18] proposed an innovative solution for resource allocation in cognitive radio networks (CRN) employing Non-Orthogonal Multiple Access (NOMA). Their two-phase optimization combines matching-based user-to-channel assignment with a Stackelberg game-driven power allocation. Simulation results show significant performance gains: a 23.6% improvement in system sum rate, a 12.6% increase in user fairness, and a 2.1% reduction in outage probability compared to conventional methods.

Fadhil et al. [19] present a Nash Bargaining Solution-based power and channel allocation method for 5G multicarrier cooperative NOMA with full-duplex beamforming. The approach ensures fairness among users with diverse channel conditions while optimizing overall system performance. Using signal-to-leakage-based precoding, the scheme achieves a 2 dB signal-to-noise ratio gain over non-cooperative systems and a 3 dB gain over multiple-input multiple-output NOMA (MIMO-NOMA), along with a high fairness index of 0.8401, due to improved interference handling and cooperation. Rathi and Gupta [20] review resource allocation methods for D2D communication, highlighting both game-theoretic and non-game-theoretic approaches. They discussed D2D benefits, including improved spectrum utilization and reduced latency, as well as challenges such as interference. Zhang et al. [21] proposed a distributed beam-scheduling method for 5G mmWave networks in which BSs share spectrum without central control. Using Lyapunov optimization and non-cooperative game theory, they model BSs as players in a game and find a Nash Equilibrium to optimize power and scheduling. Simulations show that their approach outperforms existing methods in terms of network utility. Ta et al. [22] presented a game-theoretic framework for collaborative and distributed power control in wireless networks where users share the same frequency band. Their approach enables users to collaborate by sharing information, thereby optimizing both individual and collective performance. The solution diversity and search space of the algorithm are limited due to an uneven balance between exploration and exploitation. Pandey et al. [23] proposed a game-theoretic framework to enhance spectral and energy efficiency in D2D communication within 5G-IoT networks. The study introduces a self-centered game-based algorithm for selecting brilliant mode and integrates a Support Vector Machine to enable rapid decision-making.

Coalition game theory focuses on how groups of players (coalitions) can collaborate to achieve shared goals and split rewards relatively [24]. It analyzes how cooperation benefits each member and ensures no player has an incentive to leave the group. This theory is instrumental in resource-sharing scenarios where collective action leads to better outcomes. It emphasizes stability, fairness, and mutual gain [25]. Qi et al. [26] proposed a Coalitional Game-Theoretic Power Allocation framework for distributed antenna systems, aiming to enhance downlink throughput in communication and radar networks. González et al. [27] explored enhanced dynamic radio access network selection, an innovative network selection method for 5G-advanced heterogeneous networks utilizing federated deep quality networks and cooperative game theory. Integrated into the open radio access network (O-RAN) framework, it dynamically selects BSs to optimize QoS and resource utilization. In overload situations, cooperative game theory ensures fair load balancing, but computation time for the optimization is higher. Zhang et al. [28] suggested a joint unmanned aerial vehicles deployment, power allocation, and coalition formation strategy to enhance uplink security in heterogeneous networks. Using cooperative jamming and game theory, the method boosts secrecy rates through a two-layer optimization process. However, effectiveness is limited by dynamic network conditions.

Abd Al Khalek et al. [29] explored power allocation in NOMA-based 5G networks using a Stackelberg game theoretic approach (SGTA) framework to manage network slicing for ultra-reliable low-latency communication (URLLC) and enhanced mobile broadband (eMBB) services. In this model, BSs for each slice serve as leaders, while users are considered followers, enabling hierarchical decision-making. The proposed approach aims to reduce latency for URLLC users and enhance data throughput for eMBB users. Simulation results show that the Stackelberg-based strategy efficiently balances power allocation to meet the distinct performance needs of both slices. Sun et al. [30] proposed a game-theoretic framework to enhance multi-priority data transmission in 5G-enabled vehicular networks. Their method focuses on optimizing mode selection and power control to improve system throughput while addressing the varying latency demands of different vehicular applications. The approach employs a segmented auction strategy with reserve pricing for mode selection and utilizes a Stackelberg game to manage co-channel interference. Simulation results demonstrate that their solution achieves higher throughput, greater resource efficiency, and fewer QoS violations than existing methods. Qi et al. [31] proposed a Stackelberg game-based model for optimal power allocation in heterogeneous networks. The approach addresses the leader-follower dynamics between macro BSs and small cells to manage interference and ensure efficient power use. Simulation results confirm that the strategy significantly enhances system performance and maintains network stability. Yuan et al. [32] introduced an iterative matching-SGT (IMSGT) for joint channel and power allocation in D2D underlaid cellular networks. The framework models BSs as leaders and D2D users as followers to allocate resources efficiently while minimizing interference. Their method achieves high spectral efficiency and reliable communication through repeated interactions. Liu et al. [33] proposed a reinforcement learning-based spectrum sensing method that utilizes a multislot double-threshold approach in conjunction with Bayesian data fusion. Designed for industrial big data applications, the technique enhances detection accuracy and reduces false alarms in dynamic spectrum environments.

Based on the comprehensive survey, several generalized research gaps emerge in the domain of game-theoretic approaches for power allocation in 5G and beyond wireless networks.

- Poor solution diversity, inferior balance in the exploration and exploitation strategy in game theory, leads to a poor optimal solution.
- Coalition game theory emphasizes group cooperation but faces challenges in dynamic coalition formation, fairness assurance, and practical implementation in real-time systems.
- The traditional game approaches have poor convergence, which leads to a longer time for getting an optimal solution.
- Stackelberg games offer hierarchical decision-making, which is particularly suited for network slicing and user prioritization. However, most studies consider static leader-follower roles, overlooking the dynamic role transitions that occur in evolving networks.
- There is limited work that effectively integrates hybrid game models combining cooperative and non-cooperative strategies to balance autonomy and coordination.
- The adaptation of game-theoretic models for emerging paradigms such as ultra-reliable low-latency communication, massive IoT, and mmWave communications is still in its infancy, calling for further exploration of scalable, distributed, and intelligent frameworks for power allocation.

3. METHODOLOGY

3.1 System model

The network models consist of three layers: the radio network controller (RNC) is located in the first layer, the BSs in the second layer, and the end users in the third layer. The improved SGT algorithm is utilized between layers one and two, where the RNC plays the role of leader, and the BSs play the role of followers to the leader. The RNC determines the prices for the BSs, and the BSs optimize their power accordingly. The NCG scheme is used by end users who plan their strategy to optimize power allocation based on the power allocated by the BSs of the second layer. The network model is illustrated in Figure 1.

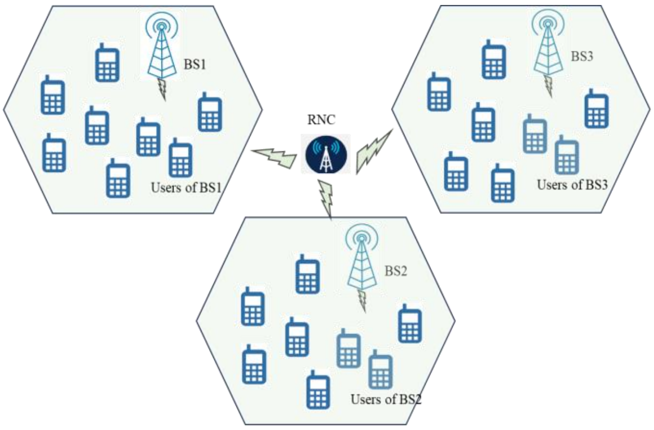

Figure 1. The illustration of the network model
Note: BS: base station; RNC: radio network controller

3.2 Proposed improved Stackelberg game theory algorithm

The SGT strategic paradigm involves the leader making a choice first and the followers responding to it. Many real-world situations, such as market pricing or wireless network resource allocation, involve hierarchical setups in which dominant entities affect others [34]. The leader predicts followers' responses and adjusts their approach to win. Consideration of choice interdependence helps this approach maximize results. In wireless communication, it can effectively handle power control or spectrum sharing. When developing distributed, coordinated systems with defined roles and responsibilities, the Stackelberg structure helps [35].

The communication network uses orthogonal frequency-division multiplexing access, in which BS operators transmit data on a shared frequency band. Multiple users from the same BS cannot acquire the channel resource simultaneously, and only the active user is allowed to transmit data to the BS. The BS decides its optimal power based on the price suggested by the RNC. The end users attain the Nash Equilibrium using NCG and acquire transmission power. The RNC further updates the prices based on optimal power. The user's Signal to Noise Interference Ratio (SINR) is given in Eq. (1).

$$\gamma_i = \frac{p_i h_{ii}}{n_O + p_O h_{iO} + \sum_{j\neq i, j=1}^{N} p_j h_{ij}} \tag{1}$$

Here, P_i and P_j indicate the power of BS i and j, respectively. P_0 stands for RNC transmission power, h_{ii} indicates the interference channel gain (ICG) between BS i and its users, h_{i0} signifies the ICG between BS and RNC, h_{ij} denotes ICG between j BS and end users of i BS, n_O symbolizes the noise power, and N stands for the total number of BSs.

RNC sets the prices to BSs to limit user interference. Pricing that is too low and excessive BS power can create interference. RNC will raise its price for its gain, and BS power will be lowered. The interaction between RNC pricing and BS power creates an SGT. BSs choose appropriate tactics based on the RNC's pricing. The Nash Equilibrium is achieved through negotiations between NCGs, resulting in an optimal transmission power. The optimal transmission power determines the RNC's ideal pricing. At this point, the system is stable. The ideal pricing and transmission power together form the equilibrium solution of the game. The utility function for the user i is given by Eq. (2), where, λ_i symbolizes the RNC price for BS and w_i indicates the transmission bandwidth of the channel.

$$\mathrm{U}_i(p_i,\lambda_i) = w_i \log_2\left(1+\frac{p_i h_{ii}}{n_O + p_O h_{iO} + \sum_{j\neq i, j=1}^{N} p_j h_{ij}}\right) - p_i . \lambda_i \tag{2}$$

Meanwhile, the RNC must assign appropriate prices to minimize interference for users. The RNC's utility function is presented in Eq. (3).

$$\mathrm{U}_{RNC}(\lambda_i) = -\sum_{i=1}^{N} p_i^*(\lambda_i) h_{Oi} \tag{3}$$

The link gain between BS and RNC (h_{i0}), BS i and its user (h_{ii}), and BS j and BS i's user (h_{ij}) are given in Eqs. (4)-(6) respectively. Here, K_{i0} indicates transmission loss between BS and RNC, K_{ii} denotes transmission loss between BS and its user, and K_{ij} signifies transmission loss between BS and users of other BS. Similarly, h_{i0} indicates transmission loss between BS and RNC, h_{ii} denotes transmission loss between BS and its user and h_{ij} signifies transmission loss between BS and users of other BS.

$$h_{i0} = K_{i0} + 35log_{10}(d_{i0}) \tag{4}$$

$$h_{ii} = K_{ii} + 35log_{10}(d_{ii}) \tag{5}$$

$$h_{ij} = K_{ij} + 35log_{10}(d_{ij}) \tag{6}$$

The RNC optimization problem aims to maximize the RNC utility function, as given in Eq. (7). It ensures the QoS during data transmission from BS i to its associated users, considering the lower bound (R_i^L) and upper bound (R_i^{U}) of transmission rate.

$$\begin{gathered}\max \mathrm{U}_{RNC}(\lambda_i) = -\sum_{i=1}^{N} p_i^*(\lambda_i) h_{Oi} \\ \mathrm{s.t.}\, R_i^L \leq R_i \leq R_i^{\mathrm{U}}\end{gathered} \tag{7}$$

The BS optimization problem is given by Eq. (8).

$$\begin{gathered}\max \mathrm{U}_i = w_i \log_2\left(1+\frac{p_i h_{ii}}{n_O + p_O h_{iO} + \sum_{j\neq i, j=1}^{N} p_j h_{ij}}\right) - \lambda_i p_i \\ s.t.\, 0 \leq p_i \leq p_i^{max}\end{gathered} \tag{8}$$

Eqs. (7) and (8) are the building blocks of a Stackelberg game method. RNC will establish fair charges for the BSs after it has developed the best BS approach. Based on the RNC's approach, the BSs will modify their own transmission power. They will then implement equivalent techniques to optimize their own transmission power. Users then get the best transmission power for a given price when the NCG reaches the Nash Equilibrium. Iteration may yield the ideal power, after which the RNC-set BS pricing can be reached, and the system as a whole approaches the Stackelberg equilibrium.

An improved SGT that uses HJB to enhance solution diversity and convergence in traditional SGT, thereby enabling EWPS to improve the exploration-exploitation balance and the search space for optimal power allocation in 5G networks. The strategies are chosen based on a random number. For 95% population, followers are updated using HJB, and for 5% weak population is updated using the EWPS scheme as given in Figure 2.

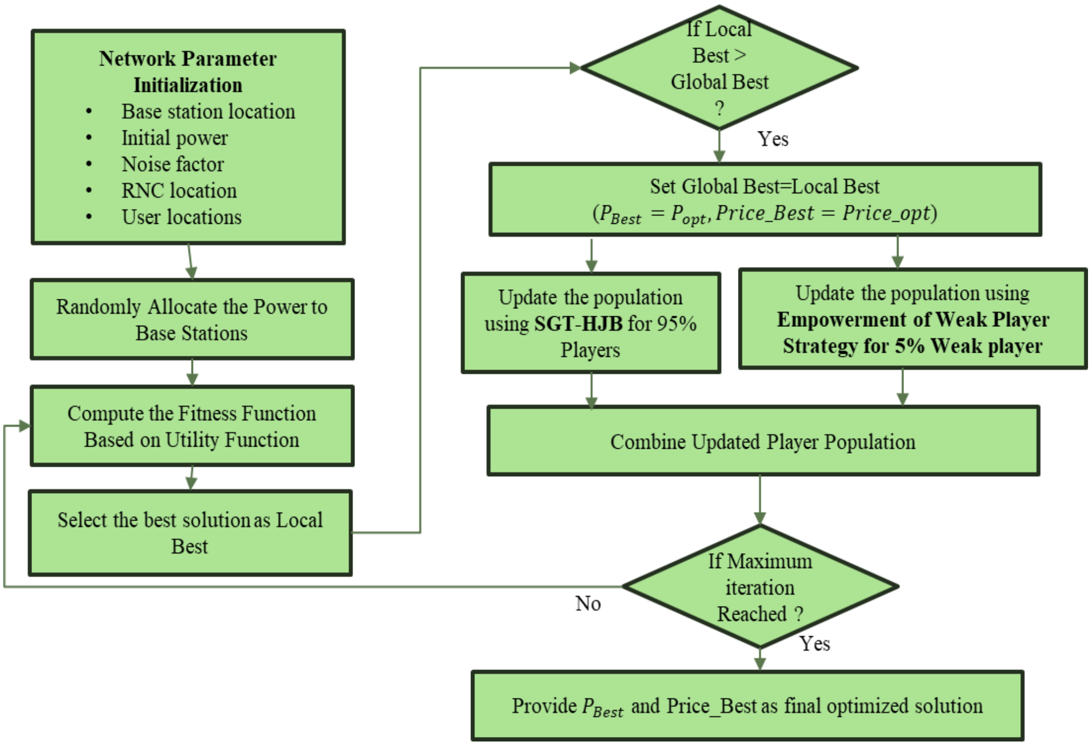

Figure 2. Flow chart of the improved SGT algorithm for power optimization

Note: HJB: Hamilton–Jacobi–Bellman; SGT: Stackelberg game theory

Power optimization using improved HJB for BS i is given by Eq. (9), which depends upon the utility function and Hamilton gradient, where η is the learning rate (step size) that lies between 0.01 and 0.1 [36, 37].

$$P_{opt}(t) = [\mathrm{P}_i + \eta.\nabla H(P)] \tag{9}$$

The Hamilton gradient ($\nabla H(P)$) is given by the following Eq. (10), where α is the system decay rate considered between 0 and 1, P_i is allocated power to i^{th} BS, U_i is the utility function for BS.

$$\nabla H(P) = \frac{dH}{dP} = -\alpha P_i + \mathrm{U}_i(p_i, \lambda_i) + (-\alpha P_i + \mathrm{U}_i(p_i, \lambda_i)) \tag{10}$$

Power optimization using the EWPS strategy is given by Eq. (11) where P_{iw} represents a weak member power (with the lowest utility value) with suboptimal transmission power, allowing it to adapt by learning from the best-performing member P_{Best}. The update shifts the weak member's power either closer to or slightly away from the best solution, depending on the random factor $r1$, promoting gradual improvement. This helps the weak user reduce interference and enhance performance while contributing to overall network efficiency in 5G.

$$P_{opt} = P_{iw} + r1 * (P_{iw} - P_{Best}) \tag{11}$$

The algorithm for the proposed method is given as follows:

Algorithm: Improved Stackelberg game theory

Input: Base station location, initial power, noise factor, radio network controller location, user locations

Output: Optimal transmission power and price

Step 1: For each user, compute the Signal to Noise Interference Ratio

Step 2: Followers (users) compute their utility response

Step 3: For each base station (Leaders)

Leaders (base stations) update power $\boldsymbol{P\_opt}$ to maximize their utility

if $\boldsymbol{P\_opt} < \boldsymbol{P\_Best}$ then

$\boldsymbol{P\_Best} = \boldsymbol{P\_opt}$

$\boldsymbol{Price\_Best} = \boldsymbol{Price\_opt}$

else

Apply the Hamilton–Jacobi–Bellman equation for updating power

Step 4: Apply the empowerment of the weak follower strategy scheme for updating power

end

end

Step 5: Repeat Steps 2-3 until the maximum iterations are reached.

4. RESULTS AND DISCUSSION

The suggested system is simulated using MATLAB R2024b on a personal computer system with 16 GB of Random Access Memory and an Intel Core i5 processor. The simulation parameters used to develop the proposed model are listed in Table 1.

Table 1. Simulation parameter configurations

Parameter	Value
Transmission bandwidth	10 KHz
Noise spectrum density	-116 dBm/Hz
Transmission of the radio network controller	45 dBm
K_{ij}	28 dB
K_{ii}	37 dB
K_{i0}	28 dB
Number of base stations	15
Radio network controller power	45 dBm
Base stations power	20 dBm

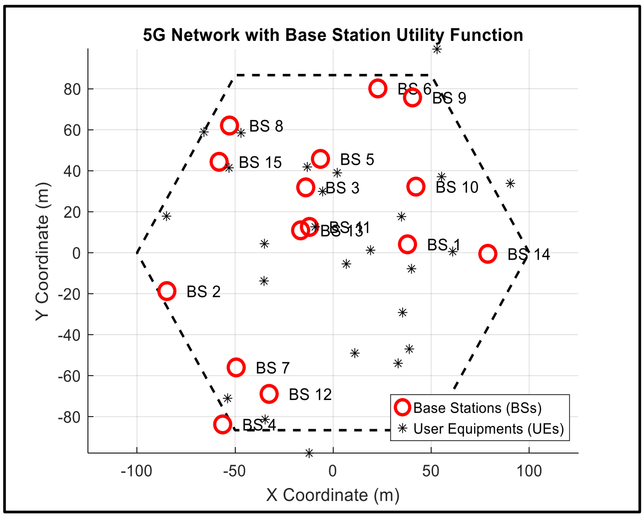

Figure 3. Network scenario for the proposed model

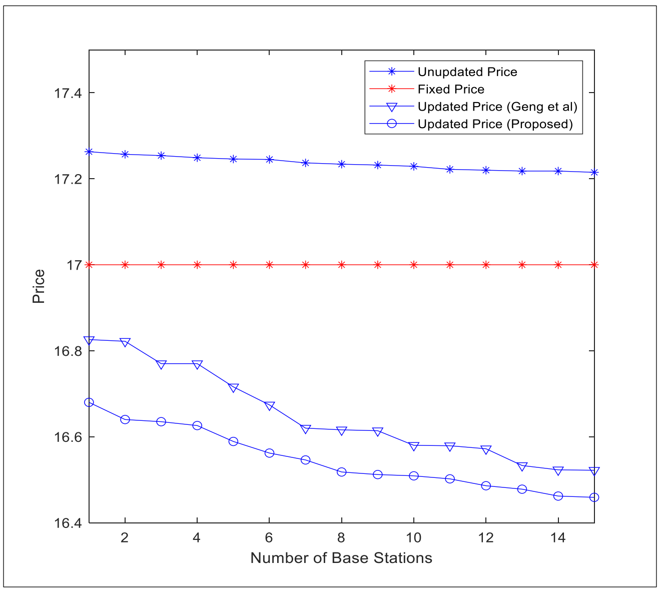

Figure 4. Performance of the proposed system for the radio network controller price vs. the number of base stations

The network scenario for the proposed network model is shown in Figure 3, where 15 BSs are considered over a single hexagonal cell with associated users over the simulation area. In fixed, unupdated pricing schemes, the RNC sets a uniform price for all BSs, causing some BSs to reduce their power unnecessarily, even at low interference levels. In contrast, the pricing update scheme assigns prices based on each BS's interference, which varies with distance. This ensures balanced transmission performance. After receiving the price, each BS adjusts its power, and the RNC updates the pricing accordingly to optimize both power and cost.

Figure 4 presents a comparison of four different pricing strategies, including Unupdated Price, Fixed Price, Updated Price (Chen et al. [14]), and Updated Price (Proposed), across 15 BSs in a 5G network. The Fixed Price remains constant at 17 for all BSs, indicating no responsiveness to varying network conditions. The Unupdated Price shows a slight downward trend from 17.263 to 17.215, reflecting minimal dynamic behaviour without optimization.

The Updated Price by Chen et al. [14] shows a more substantial reduction from 16.826 to 16.522, indicating moderate adaptability. However, the proposed algorithm achieves the most efficient and consistent decrease, starting at 16.680 and reaching a low of 16.459. This indicates superior adaptability and cost-effectiveness. Compared to the other methods, the proposed strategy offers the lowest prices while accounting for interference and distance variations more effectively. Overall, the statistical trend clearly indicates that the proposed pricing update method yields the best performance by reducing costs and improving resource allocation across BSs.

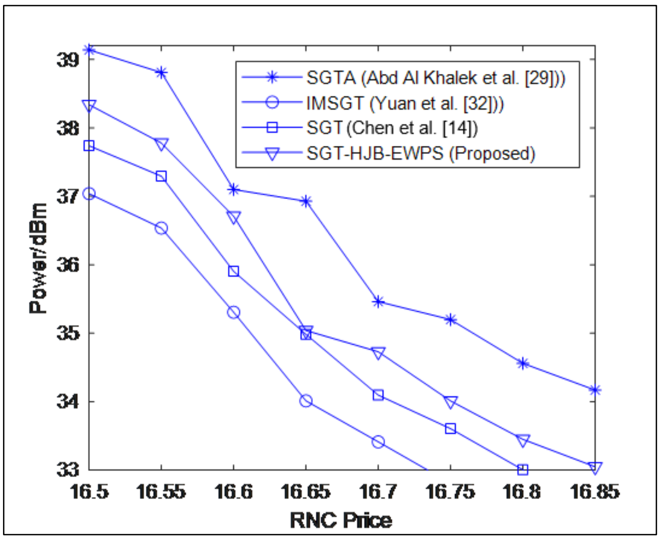

Figure 5. Performance of the proposed system for radio network controller price vs. power allocation

Interference prices correlate with distance; closer BSs face higher interference and costs, while distant ones benefit from lower prices due to reduced interference. When the iteration eventually achieves a stable state, the price that RNC charges for each BS is shown in Figure 5.

Furthermore, it demonstrates that the BS will incur additional costs due to interference resulting from the rising RNC price. The utility function of the BS will be reduced as a consequence of this, and due to this, the transmission power of the BS will eventually decrease. The performance is compared with the traditional SGT given by Chen et al. [14]. Both power update methods exhibit a downward trend as the RNC price increases, indicating that higher pricing encourages users to reduce their transmission power to minimize costs. The study [14]'s method begins at approximately 39.14 dBm and gradually reduces to approximately 34.17 dBm, resulting in a total reduction of roughly 5 dBm. In contrast, the proposed method starts at a lower power value of 38.34 dBm and decreases more steadily to 33.05 dBm, resulting in a greater total reduction of approximately 5.29 dBm. The proposed method achieves approximately 3–4% power reduction compared to the SGTA [29] method and around 2–3% improvement over SGT [14] and IMSGT [32] techniques. It likely provides enhanced interference control and energy efficiency in the network compared to the method of Chen et al. [14]. Moreover, the consistent gap between the two curves suggests that the proposed strategy maintains lower power consumption across all price points, showcasing its superiority in dynamic power allocation.

Figure 6 compares the utility function values across 15 BSs for the Unupdated price, Fixed price, Updated price using SGTA [29], IMSGT [32], SGT [14], and the proposed SGT-HJB-EWPS. And an improved algorithm. Statistically, the utility function represents the system's performance, which increases with the number of BSs due to better resource allocation and pricing mechanisms. Among all strategies, the SGT-HJB-EWPS shows the highest utility values, starting at 330 for a single BS and reaching 399 for 15 BSs. This reflects consistent and superior utility enhancement compared to others. The SGT-HJB-EWPS achieves a higher utility of 399 than 387 of SGTA [32], 378 of IMSGT [29], and 395 of SGT [14] for 15 BSs. The updated price [14] method also performs well, ranging from 328 to 398, closely following the improved approach but slightly lower at each point. The Fixed price method shows a moderate increase, starting from 324 and ending at 375.

The outdated price strategy lags, ranging from $320 to $371. This indicates that without price adaptation, the utility function grows more slowly and is suboptimal.

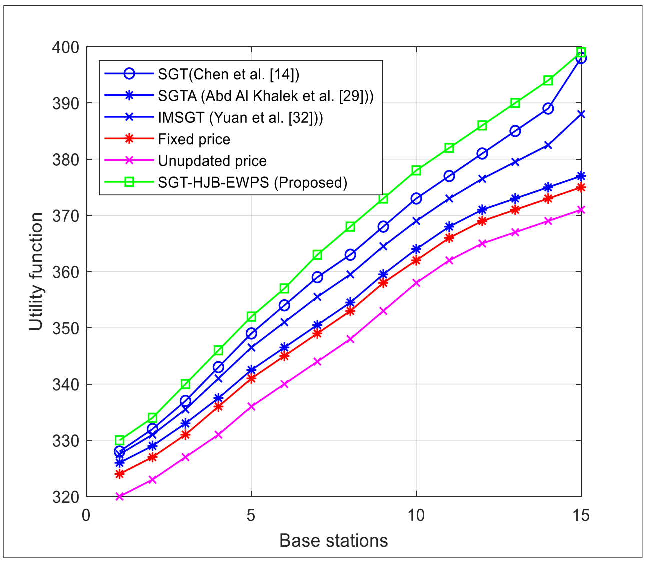

Figure 6. Utility function value for different algorithms and base stations

The convergence of the proposed algorithm is shown in Figure 7, which depicts the proposed SGT with HJB and EWPS over 10 iterations. The algorithm achieves a superior normalized SINR for SGT-HJB-EWPS than SGT [14], SGTA [29], and IMSGT [32], thereby improving solution diversity and balancing exploration and exploitation relative to the traditional SGT algorithm. The normalized SINR is computed using z-score normalization. The better convergence leads to a superior solution in fewer iterations.

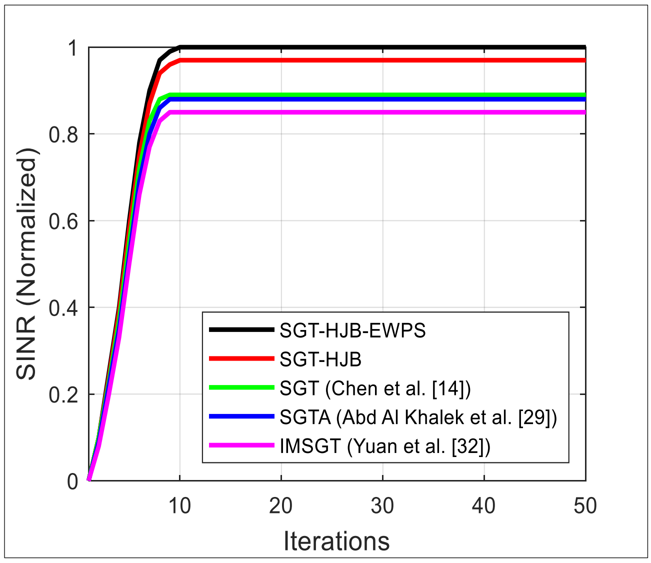

Figure 7. Convergence comparison of the algorithm

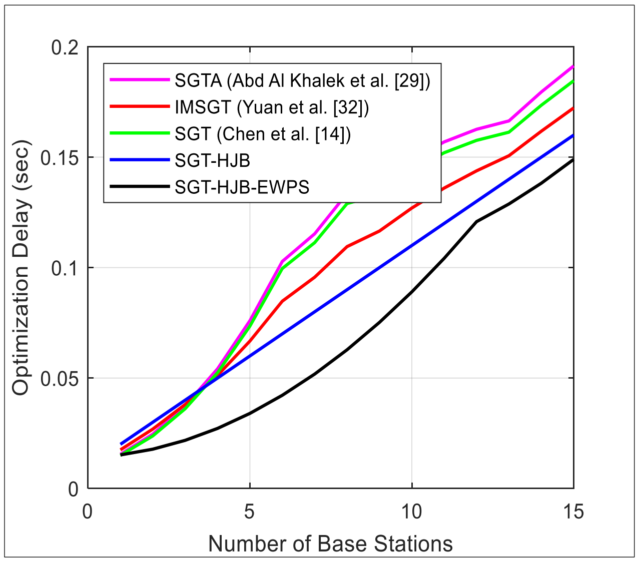

Figure 8. Optimization delay visualization for different power optimization algorithms

Table 2 and Figure 8 present the delay required to obtain the optimized power allocation for the three algorithms: SGT [14], SGTA [29], IMSGT [32], SGT-HJB, and SGT-HJB-EWPS. The delay is computed for considering different numbers of BSs. The results indicate that delay generally increases with the number of BS due to the higher computational and communication complexity involved. This trend highlights that while SGT exhibits rapid delay growth as BS increases, integrating HJB reduces the computational burden, and the enhancement with EWPS further optimizes performance.

Table 2. Optimization delay for power optimization for different algorithms

Number of BS	Optimization Delay (sec)				
	SGTA [29]	IMSGT [32]	SGT [14]	SGT-HJB	SGT-HJB-EWPS
1	0.0155	0.0159	0.0150	0.0200	0.0152
2	0.0246	0.0252	0.0238	0.0300	0.0178
3	0.0374	0.0384	0.0361	0.0400	0.0218
4	0.0542	0.0555	0.0524	0.0500	0.0272
5	0.0760	0.0779	0.0735	0.0600	0.0340
6	0.1028	0.1053	0.0996	0.0700	0.0422
7	0.1153	0.1178	0.1113	0.0800	0.0518
8	0.1336	0.1364	0.1290	0.0900	0.0628
9	0.1376	0.1406	0.1331	0.1000	0.0752
10	0.1488	0.1522	0.1439	0.1100	0.0890
11	0.1569	0.1605	0.1520	0.1200	0.1042
12	0.1626	0.1664	0.1576	0.1300	0.1208
13	0.1664	0.1703	0.1613	0.1400	0.1288
14	0.1795	0.1836	0.1735	0.1500	0.1382
15	0.1913	0.1958	0.1846	0.1600	0.1490

Note: BS: base station; SGT: Stackelberg game theoretic; SGTA: SGT approach; IMSGT: iterative matching-SGT; HJB: Hamilton–Jacobi–Bellman; EWPS: Empowerment of Weak Player's Strategy

The SGT-HJB-EWPS requires 0.1490 sec to obtain the optimal power allocation, which is lower than that of the traditional SGT (0.1846 sec) and SGT-HJB (0.16 sec) for 15 BSs. Thus, SGT-HJB-EWPS emerges as the best approach, achieving the lowest delay across all tested BS values, with improvements of around 15–20% compared to SGT for larger BS counts.

5. CONCLUSION AND FUTURE SCOPE

This study presents the optimal power allocation in the 5G network using a novel improved SGT that combines the HJB and EWPS. The improved SGT is applied between the RNC and the BSs, with the RNC acting as the leader and the BSs as followers. The RNC sets interference prices for the BSs and users in the third layer, and based on these prices, the BSs and users adjust their transmission power using NCG theory. The proposed improved SGT enhances solution diversity, convergence, exploration-exploitation balance, and search space of the traditional SGT. It helps achieve the Nash Equilibrium, which offers improved power optimization and pricing. The SGT-HJB-EWPS helps to minimize the optimization time by 15–20% and reduce the price by 3.94% for power allocation compared to the traditional SGT.

In the future, the focus can be on traffic patterns (periodic, aperiodic, and deterministic) and device types (eMBB, URLLC, massive IoT) for power allocation in 5G networks. In the future, effectiveness can be improved by using deep reinforcement learning techniques for power optimization to handle larger user bases and higher bandwidths, as well as to handle larger traffic and higher network loads.

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