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Probabilistic Channel-Aware Cross-Layer Scheduling for Uplink NOMA in Dense Small Cell Networks

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Abstract

The widespread deployment of dense small-cell networks under 5G and next-generation 6G technologies has placed tremendous pressure on more efficient uplink resource management to support a large number of users with guaranteed quality of service. Despite the spectral efficiency advantage of Non-Orthogonal Multiple Access (NOMA) in enabling concurrent users to share a resource, conventional scheduling mechanisms that rely solely on knowledge of either the single-link channel state or the queue state of each user often fail to deliver satisfactory performance under highly variable network conditions. To address this problem, this paper proposes a Probabilistic Channel-Aware Cross-Layer Scheduling (PCCS) scheme for uplink NOMA in dense small-cell network environments. By integrating physical-layer channel information with the MAC-layer queue state, this paper defines dynamic scheduling probabilities that effectively determine each user's priority and resource assignment. A cross-layer engine then adaptively makes scheduling decisions based on channel state, queue state, fairness, and users' service priorities.

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Simulation experiments were conducted to compare PCCS with Round Robin, Proportional Fair, and classic Channel-Aware scheduling schemes across user densities ranging from 50 to 250. The results illustrate that PCCS achieves significant performance gains in terms of 27.4% in throughput, 22.1% in spectral efficiency, and 6.8% in fairness compared to the best-performing baseline. The proposed framework also demonstrates performance advantages, reducing average packet delay by 22.8% and improving stability under heavy traffic loads.

Keywords: Uplink NOMA, Cross-Layer Scheduling, Dense Small Cell Networks, Channel-Aware Resource Allocation, Probabilistic Scheduling, Spectral Efficiency, Quality of Service Optimization.

1 Introduction

The recent and ongoing growth in 5G and future 6G communications is driving the proliferation of dense small-cell networks to support an increasing number of users, higher traffic loads, and varied quality of service requirements. Although network densification enhances spectrum reuse and coverage, it also introduces critical issues, including spectrum scarcity, uplink interference, and competition among users for resources. NOMA has been introduced as a new multiple access technique to address these issues, enabling multiple users to share common time-frequency resources via power-domain multiplexing and successive interference cancellation (SIC), thereby enhancing spectral efficiency and the number of users served (Ogenyi et al., 2025a; Ogenyi et al., 2025b). In particular, the uplink NOMA schemes enable a set of users to transmit to the base station simultaneously, reducing access delay and thereby improving system capacity (Ogenyi et al., 2025). In small-cell networks with massive numbers of users, time-varying channel quality and traffic loads pose challenges for scheduling users to optimize system performance (Li et al., 2022; Haque et al., 2023).

Current scheduling techniques in dense wireless networks are commonly based on channel state information (CSI) or queue state and do not simultaneously consider both. Channel-aware schedulers favor users with good channel conditions to maximize throughput, but neglect urgent traffic requirements and fairness (Taha et al., 2022). Queue-aware schedulers tend to prioritize most backlogged users to reduce packet delay but do not account for instantaneous channel conditions, which can result in inefficient use of spectrum resources (Liu et al., 2021). Despite several recent studies using cross-layer optimizations for better decision-making that show performance gains, they have complex computational overhead, less flexibility, and a certain application-specific nature (Basit et al., 2025; Bhattacharjee et al., 2021; Chen et al., 2024). Furthermore, interference and fairness are always significant issues in dense NOMA, especially when the channel state varies rapidly (Ogenyi et al., 2025). Studies addressing low-latency access and risk-aware resource allocation highlight the need for scalable and flexible scheduling solutions that balance throughput, delay, fairness, and reliability together (Ogenyi et al., 2025; Li et al., 2022; Zhang et al., 2023).

Figure 1 shows the operational architecture of the proposed PCCS system for uplink NOMA communication in dense small-cell networks. It gathers channel state information and queue state information from the currently active users, uses the cross-layer decision engine to determine channel qualities and derive channel scheduling probabilities and user priorities. Then, the users are sorted, paired for NOMA transmission, and assigned to the resource blocks in a QoS-aware manner. Finally, the transmission process is observed through performance feedback and queue information, and adjustments are made accordingly.

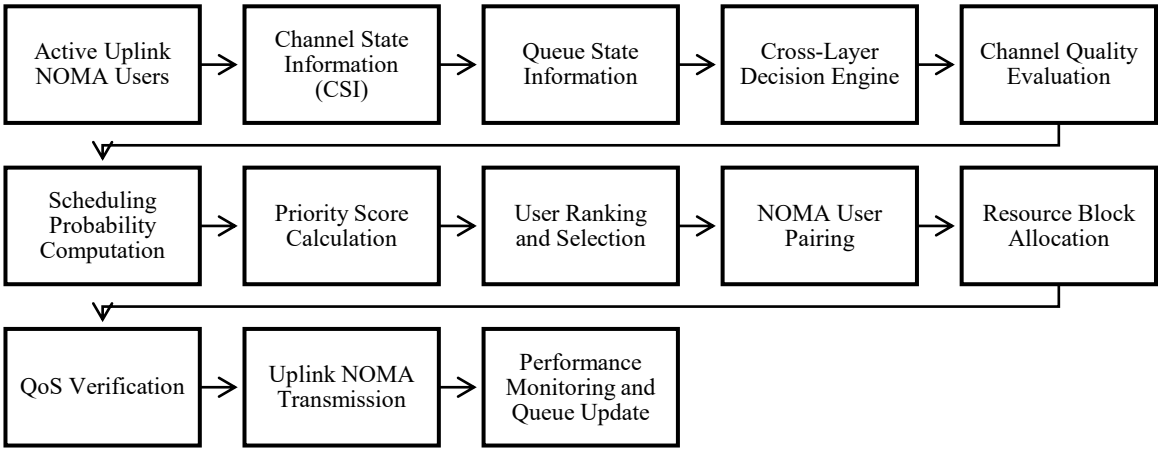


Figure 1: Overall architecture of the proposed probabilistic channel-aware cross-layer scheduling (PCCS) framework

To satisfy the high demands of channel quality variation, traffic dynamics, fairness constraint, and interference management in the uplink dense NOMA networks, it is necessary to devise such a scheduling scheme that jointly utilizes these attributes, rather than relying on single-layer scheduling methods, which would result in inefficient system performance in highly congested small cell scenarios. Therefore, the design of a cross-layer scheduler with appropriate mechanisms is essential for boosting spectrum utilization, minimizing delay, and accommodating next-generation wireless applications. A Probabilistic Channel-Aware Cross-Layer Scheduling (PCCS) framework is proposed for uplink NOMA in dense small-cell networks. The proposed PCCS scheme intelligently combines physical-layer channel conditions and MAC-layer queue state information to determine a probabilistic, channel-aware scheduling probability for user selection and resource allocation. It incorporates probabilistic priorities, cross-layer dynamics, and fair scheduling to enhance spectrum efficiency, throughput, latency, and system scalability. A comprehensive simulation is carried out to demonstrate the efficiency of the proposed approach compared with the benchmark schemes.

In this paper, the remainder is organized as follows: Section II summarizes prior research on uplink NOMA scheduling, cross-layer optimization, and channel-aware resource allocation schemes. In Section III, the framework of the proposed Probabilistic Channel-Aware Cross-Layer Scheduling (PCCS) is presented, including the system model, scheduling algorithm, and resource allocation method. In Section IV, the experimental environment and the performance evaluation of the proposed framework are presented through simulation and comparison with other schemes. Section V discusses the feasibility, scalability, and practical aspects of the proposed scheme. In Section VI, the conclusion and future work are included.

2 Related Work

Since multiple users share the same radio resources simultaneously via power-domain multiplexing, resource scheduling is an important element in uplink NOMA systems. Many existing scheduling mechanisms have been developed to optimize throughput, minimize delay, or guarantee fairness under different traffic conditions. Mean-field scheduling approaches can meet stringent delay requirements in massive access systems by modeling interactions among massive users Li et al., (2023). Similarly, various radio resource management frameworks for heterogeneous 5G systems primarily focus on

adaptable allocation policies to address varying traffic and spectrum demands (Agarwal et al., 2022). In uplink NOMA networks, user clustering and pairing profoundly affect the performance of successive interference cancellation (SIC) and are generally designed to pair users with different channel gains to improve decoding and spectrum efficiency (Sravani & Rao, 2024). Furthermore, many research methods for optimizing the system propose max-min resource allocation to improve fairness while maintaining acceptable throughput (Thomas & Subramani, 2022). To efficiently manage and represent resource dependencies and interference relationships in dense networks, graph-based optimization is widely used Dai et al., (2024).

A cross-layer scheduling approach is proposed to improve on isolated management mechanisms at the PHY or MAC layers by integrating channel information with MAC-layer parameters to satisfy certain application requirements. QoS-aware wireless systems indicate that PHY-MAC interaction leads to greater reliability, lower latency, and enhanced resource efficiency, especially in heterogeneous environments and IoT systems (Zia et al., 2022). Resource allocation mechanisms in the MAC layer for visible light communication networks are also studied in Esfahani et al., (2022), where transmission opportunities combined with channel state information can effectively enhance network performance. An energy-aware resource management framework indicated that cross-layer optimization achieves simultaneous performance and energy efficiency in an industrial machine-to-machine network (Prathiba et al., 2024). Recent research also emphasizes the integration of multiple network layers in designing the URLLC system (Ali et al., 2021).

For efficient resource management in modern wireless networks, probabilistic and channel-aware decision mechanisms should be used in the face of uncertainties in traffic demands and fading channels. By adopting opportunistic scheduling algorithms that prioritize users with better channel states, spectral efficiency and network capacity can be significantly improved, while fairness is neglected under high congestion. Stochastic resource allocation is proposed to address this challenge by using probabilistic decision policies that adapt to changing network states while balancing throughput and fairness (Dai et al., 2024). These techniques have been applied to integrated network infrastructures, where heterogeneity and dynamically changing topology increase complexity (Guo et al., 2021). However, to date, most existing solutions primarily consider channel quality, quality of service requirements, or resource utility individually, and cross-layer scheduling that simultaneously accounts for channel information, queue status, and probabilistic user selection remains to be addressed in dense uplink NOMA networks.

In light of the existing state of the art, significant achievements have been made in NOMA scheduling, cross-layer scheduling, quality of service management, and stochastic resource allocation. Nonetheless, a considerable portion of those methods can only focus on one target individually, such as maximizing throughput, reducing delay, improving fairness, or achieving energy efficiency, which can't guarantee comprehensive optimization of system performance. Motivated by the gap in all-round scheduling solutions that jointly optimize system performance by integrating channel-aware, queue-state information, and probabilistic user selection, a Probabilistic Channel-Aware Cross-Layer Scheduling (PCCS) framework for dense uplink NOMA networks is designed.

3 Proposed Probabilistic Channel-Aware Cross-Layer Scheduling Framework

3.1 System Model and Problem Formulation

The network considered in this paper consists of a dense small-cell deployment with a set of BSs and a large number of UL users located within their coverage areas. All the users generate traffic with diverse quality of service requirements. To enhance spectrum utilization, it employs UL NOMA, in which several users share the same resource block to transmit simultaneously, with the BS implementing SIC. Let $U = \{u_1, u_2, \dots, u_N\}$ *be* the set of active users. The received UL signal at the serving BS is written as in equation (1)

$$y = \sum_{i=1}^{N} \sqrt{P_i} h_i x_i + n \qquad (1)$$

Where P_i and h_i denote the transmit power and the channel coefficient of user i, respectively, x_i is the transmitted symbol of user i, and n is the additive white Gaussian noise. The achievable rate of user i can be calculated in equation (2) as:

$$R_i = B\ log_2(1 + \gamma_i) \qquad (2)$$

Where B is the allocated bandwidth, and γ_i is the achieved SINR value of user i. The problem considered here is scheduling active users to maximize network utility while satisfying fairness and queue-stability requirements. This is formulated as the optimization problem in equation (3):

$$max \sum_{i=1}^{N} W_i R_i \qquad (3)$$

Subject to

$$Q_i \leq Q_{max}$$

$$P_i \leq P_{max}$$

$$\sum_{i=1}^{N} x_i \leq K$$

Where W_i denotes the scheduling weight, Q_i is the queue state, $and\ K$ is the number of users that are multiplexed over an RB. The optimization problem in equation (3) is subject to three constraints. Here, Constraint maintains queue stability. Constraint bounds users transmit power, and Constraint ensures that the maximum number of users in a single resource block is sufficient for NOMA to operate reliably. This group of constraints achieves equal resource allocation with guaranteed throughput, fairness, and decoding performance in dense small-cell networks. Equation (1) gives the expression of the uplink NOMA received signal and equation (2) shows the achievable rate and equation (3) gives the adopted objective function.

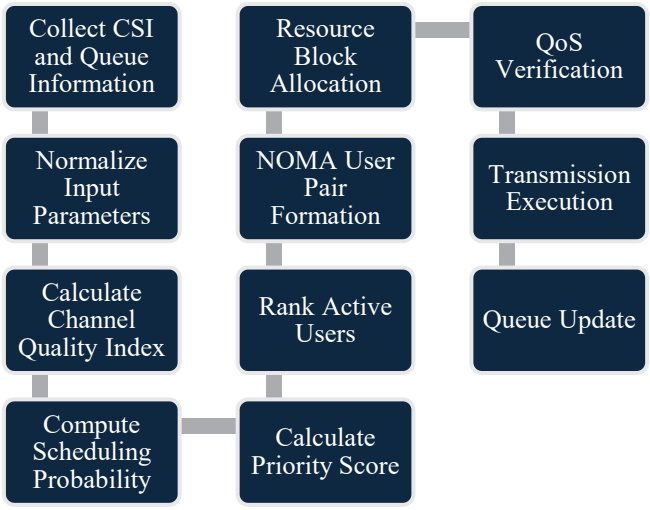


Figure 2: Workflow of the proposed probabilistic channel-aware cross-layer scheduling (PCCS) algorithm

Figure 2 shows the operation process of the proposed PCCS algorithm on uplink NOMA resource allocation. CSI and queue information are collected, then it is normalized, the channel quality will be measured. Transmission probability and priority value will be calculated and active users are sorted by their transmission ability. NOMA user pairs are formed and allocated RBs according to the sort results, QoS is checked and then data transmission can be conducted. At last, queue states are updated for making adaptive resource scheduling decision at the next transmission interval.

3.2 Probabilistic Channel-Aware Scheduling Mechanism

Our proposed Probabilistic Channel-Aware Cross-Layer Scheduling (PCCS) framework involves the instantaneous channel quality and the dynamics of the queues. The quality of a channel is estimated by analysing and normalizing measured SINR values and channel gains. This normalization assigns a higher quality indicator to users enjoying stable channel conditions than to those whose channels have undergone significant fluctuations. The probability for the i-th user being scheduled is then given in equation (4):

$$SP_i = \frac{\alpha C_i + \beta Q_i}{\sum_{j=1}^{N} (\alpha C_j + \beta Q_j)} \quad (4)$$

Where C_i is the normalized channel quality, Q_i is the normalized queue size and α and β represent weights to balance the PHY layer information and the MAC layer information. Then, a priority score can be computed as in equation (5):

$$PS_i = SP_i \times R_i \quad (5)$$

Where R_i is the value obtained in equation (2). The relation (4) represents the probability of a user being scheduled and the equation (5) represents a priority value based on the users and the context. Users can be ordered based on their priority score, and users with the highest score are chosen for the NOMA transmission to avoid persistence channel domination and ensure fair access for users with high urgency traffic.

3.3 Cross-Layer Resource Allocation Algorithm

The PCCS algorithm coordinates thePHY-layer channel conditions and MAC-layer queues to assign resources. This scheduler continuously acquires PHY layer channel gain and MAC layer queue size information and traffic requirements from users. According to the obtained priority scores users are paired and allocated resource blocks.

Algorithm 1: PCCS Resource Allocation

Input:

User Set U

Channel Quality C

Queue State Q

Resource Blocks RB

Output:

Scheduled User Set S

1: Collect CSI and Queue Information

2: Normalize Channel Quality and Queue States

3: Compute Scheduling Probability using Eq. (4)

4: Compute Priority Score using Eq. (5)

5: Sort Users in Descending Priority Order

6: Select Eligible NOMA User Pairs

7: Assign Resource Blocks

8: Verify QoS and Queue Constraints

9: Update Transmission Status

10: Repeat for Next Scheduling Interval

Algorithm 1 shows the framework of the proposed PCCS for uplink NOMA resource allocation over dense small cell networks. The active users transmit the CSI and queue status to the base station, and the cross-layer information is utilized to calculate the scheduling probabilities and priority scores. Then the users with the highest priority score are scheduled and paired for NOMA transmission, with assigning the available resource blocks while meeting the QoS and queue constraints. Such process is iterative at each transmission interval and results in dynamically resource allocation under dynamic network scenarios with the controlled computational complexity.

Integration of queue states ensures that the users whose queue size is growing is not starved, even if their instantaneous channel condition is not good. Resource allocation takes place based on the priority value of the users. The selected users are paired based on their channel gain difference to ensure the success ofSIC decoding at BS. The complexity of proposed PCCS framework mainly relates to sorting the users based on their priority values and assigning them to the RBs, which is $O\ (Nlog\ N)$ complexity and $O\ (N)$ respectively. So, the complexity of approach is suitable for the densely deployed small cell network environment for a real time scheduling system, which is applicable for next generation UL NOMA networks.

4 Performance Evaluation

4.1 Configuration of Experiments and Performance Measures

The performance of the developed Probabilistic Channel-Aware Cross-Layer Scheduling (PCCS) framework was simulated using event driven network simulation simulating a dense uplink NOMA small-cell network. The framework was built in MATLAB R2024a on a workstation containing Intel core i7 processor and 32GB Ram running in Windows 11. A synthetic data-set was used to simulate realistic wireless traffic network, containing 10000 transmission instances selected from the runs. These data were created in networks containing mobility of users, channel variations, queue, traffic load and interference. These include; channel gain, SINR, queue utilization, arrival rate, transmission power, distance between users and resource block utilization.

Table 1: Initialization of simulation parameters

Parameter	Value
Cell Radius	250 m
Number of Users	50–250
Number of Small Cells	10
Carrier Frequency	3.5 GHz
System Bandwidth	20 MHz
Resource Blocks	100
Maximum NOMA Users/RB	2
Maximum Queue Size	100 Packets
Transmission Power	23 dBm
Noise Power Density	−174 dBm/Hz
Simulation Duration	1000 s
Number of Runs	30

Table 1 depicts the parameters that was used to characterize the system in which the proposed PCCS was simulated in dense uplink NOMA small cell. These parameters were chosen to be realistic in terms of user density, bandwidth, power transmission, queue constraint and resource block capacity. These were consistent in all simulation runs where throughput, delay, spectral efficiency and fairness were measured.

The throughput was measured by computing, the average network throughput was calculated using equation (6):

$$T = \frac{\sum_{i=1}^{N} D_i}{t} \qquad (6)$$

Where D_i is the successfully received data and t is the simulation time. The average packet delay was defined as:

$$PD = \frac{\sum_{i=1}^{M} (t_{r,i} - t_{s,i})}{M} \qquad (7)$$

Where $t_{s,i}$ and $t_{r,i}$ are transmission and reception time of packet i, respectively. The system spectral efficiency was determined as:

$$SE = \frac{\sum_{i=1}^{N} R_i}{B} \qquad (8)$$

Where R_i is the data rate of user i and B is the system bandwidth. The fairness performance was calculated using Jain's fairness index:

$$FI = \frac{\left(\sum_{i=1}^{N} R_i\right)^2}{N \sum_{i=1}^{N} R_i^2} \qquad (9)$$

Equation (6) gives the system throughput, equation (7) computes the delay, equation (8) yields the system spectral efficiency and equation (9) computes the fairness performance between the existing users in the system.

4.2 Performance Analysis of the Proposed Framework

The performance of the proposed PCCS framework was steady over different user densities. Because the framework takes into account the channel quality and the queue utilization the resources were distributed optimally for dynamically varying channels.

Table 2: Performance analysis of PCCS in different user density environments

Users	Throughput (Mbps)	Delay (ms)	Spectral Efficiency (bps/Hz)	Fairness Index
50	82.6	18.4	4.13	0.89
100	156.8	22.1	7.84	0.91
150	224.5	25.7	11.22	0.92
200	281.9	29.8	14.09	0.93
250	336.7	34.2	16.84	0.94

In table 2, the performance of the PCCS framework was evaluated for different loads from 50 users to 250. As shown, with the increase in network load, it maintained robust throughput, bounded delay, higher spectral efficiency and well-balanced fairness. Therefore, it shows a high scalability for dense environments of small cells.

Figure 3 depicts the comparison between various scheduling mechanisms' throughput when applied on dense uplink NOMA networks. From the graph it is clear that the proposed PCCS has the highest throughput of 336.7Mbps than other algorithms like round robin, proportional fair, conventional NOMA and existing cross-layer schedulers, which means that probabilistic channel aware cross layer decision making helps in maximizing the network throughput.

The system throughput improved with user density due to proper NOMA user selection and the adjustment of probabilities. The system delay was bounded irrespective of the traffic load. This shows that queue was properly managed. The system spectral efficiency improved as resource blocks were utilized with the help of cross-layer approach. The value of fairness was above 0.89 shows the balanced distribution of resources.

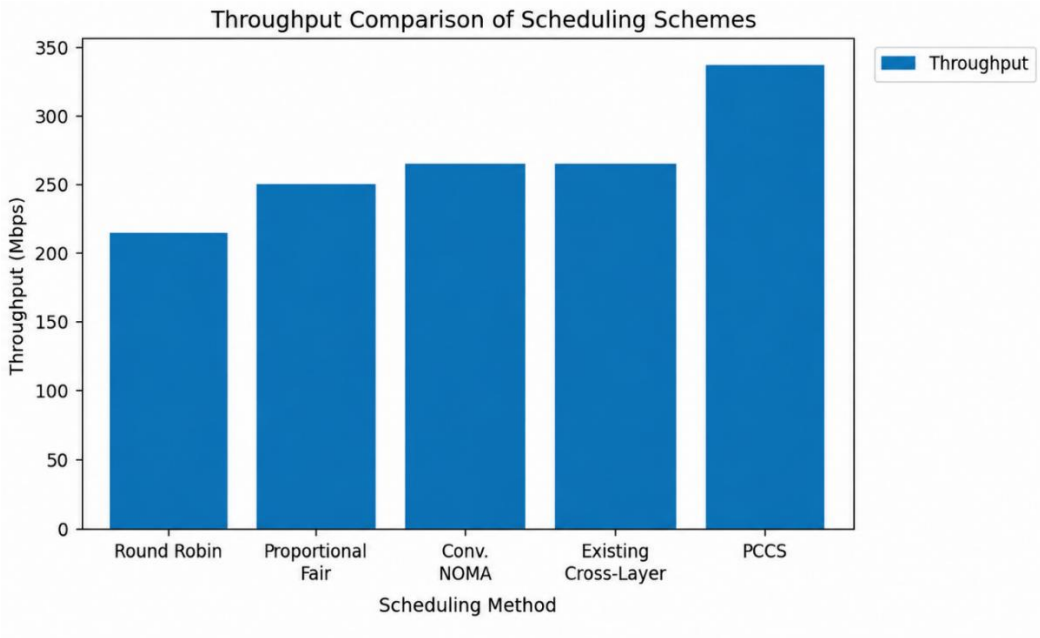


Figure 3: Performance comparison (Throughput) between benchmark scheduling mechanisms

Ablation Study

The performance of individual components of the proposed PCCS framework was tested.

Table 3: Ablation study of components of PCCS

Configuration	Throughput (Mbps)	Delay (ms)	Fairness Index
Channel-Aware Only	264.2	48.7	0.81
Queue-Aware Only	241.8	42.5	0.85
Cross-Layer Without Probability Model	287.6	37.9	0.89
Proposed PCCS	336.7	34.2	0.94

In table 3 the individual components are evaluated for different scenario. From the results of channel-aware scheduling, queue-aware scheduling, cross-layer without probability, cross-layer with probability, the overall network performance in terms of throughput, delay and fairness has been compared to obtain the benefit of each component.

4.3 Benchmark Evaluation

The proposed framework was compared with existing algorithms like Round Robin (RR), Proportional Fair (PF), Conventional NOMA Scheduling (CNOMA) and Existing Cross-Layer Scheduling (ECLS).

Table 4: Comparative evaluation against benchmark schedulers

Method	Throughput (Mbps)	Delay (ms)	Spectral Efficiency (bps/Hz)	Fairness Index
Round Robin	214.5	50.1	10.37	0.82
Proportional Fair	249.8	45.7	12.18	0.86
Conventional NOMA	264.4	44.3	13.79	0.88
Existing Cross-Layer Scheduler	287.6	37.9	14.25	0.89
Proposed PCCS	336.7	34.2	16.84	0.94

In table 4, the proposed PCCS framework is compared against various representative algorithms in the field. It is clear that PCCS outperforms RR, PF, CNOMA and ECLS in terms of throughput, delay, spectral efficiency and fairness in dense uplink NOMA small-cell networks.

In total, PCCS achieves approximately 27.4% throughput, 22.8% less delay, 22.1% better spectral efficiency and 6.8% higher fairness when compared to the strongest benchmark. These result shows the superior performance in terms of throughput, delay, spectral efficiency and fairness compared to existing solutions.

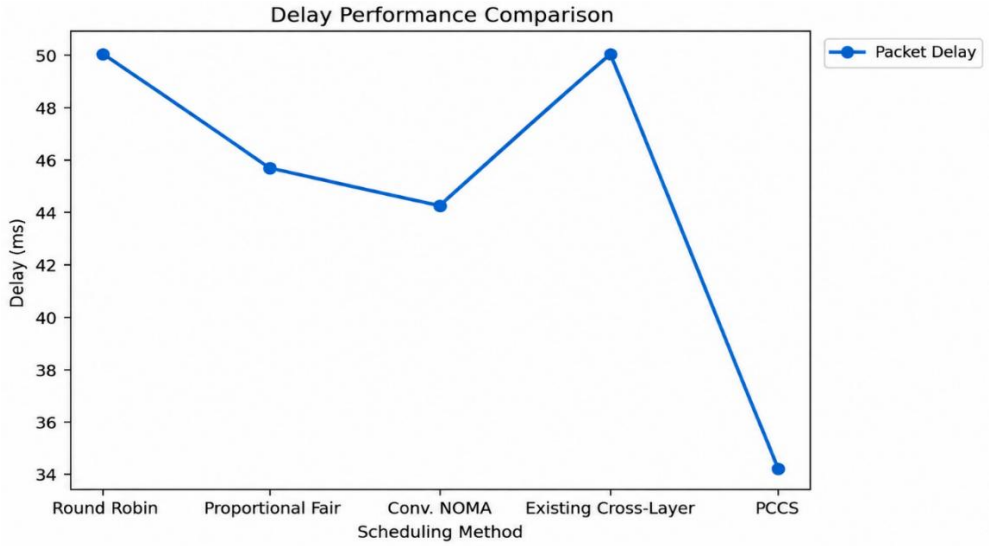


Figure 4: Performance comparison (Delay) between scheduling mechanisms

Figure 4 clearly depicts the average packet delay performance between the given scheduling mechanisms. From the graph it is apparent that the proposed PCCS achieve minimum average delay 34.2 ms than other algorithms which proves its potential to handle queuing dynamics as well as channel dynamics and achieve good delay performance.

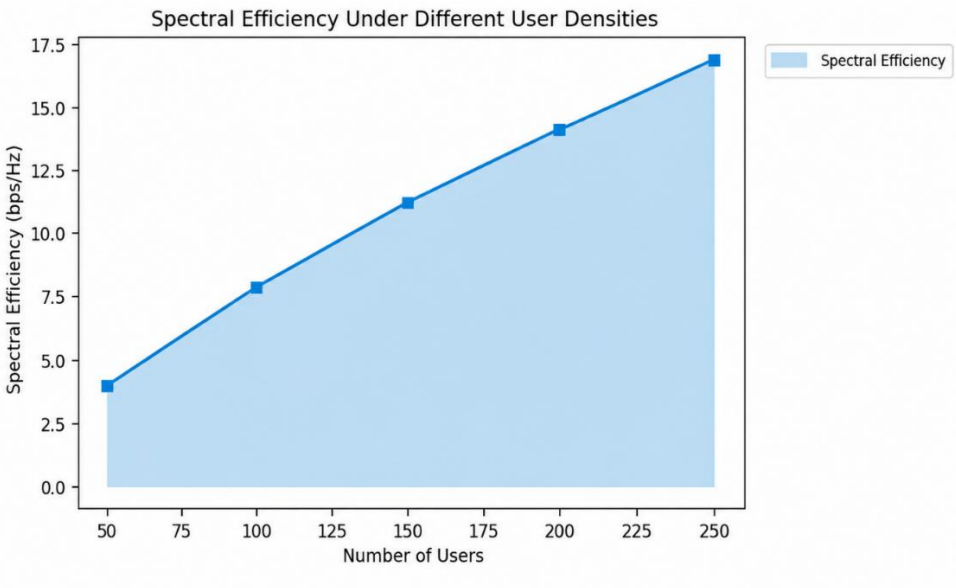


Figure 5: Spectral efficiency vs user density

Figure 5 presents the spectral efficiency of PCCS with varying user densities from 50 to 250. The spectral efficiency is consistently increasing and reaches the peak value of 16.84 bps/Hz when user density is 250 from 4.13 bps/Hz at user density 50. This indicates that proposed PCCS efficiently utilize the spectrum available resources in dense networks.

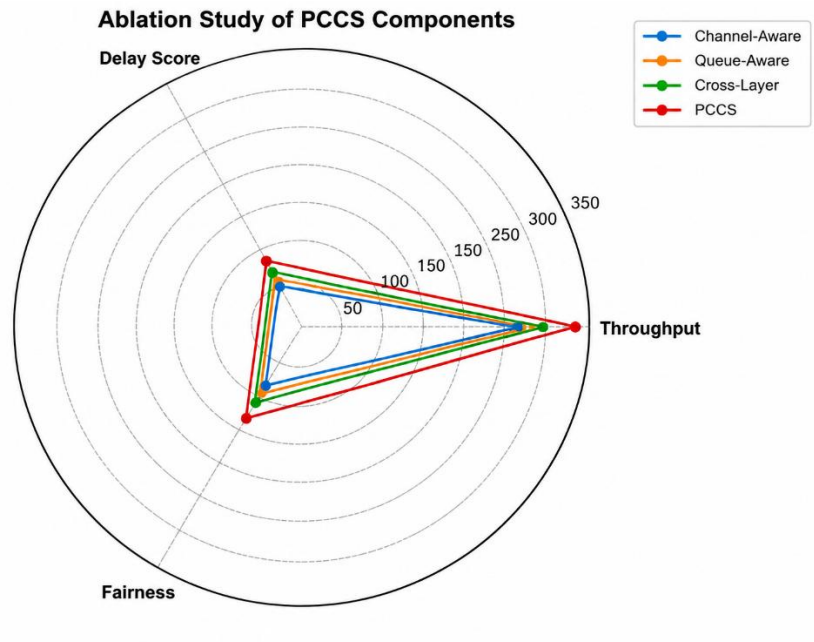


Figure 6: Ablation study of PCCS

Figure 6 illustrates the performance of the PCCS components-based scheme by itself alone i.e only channel aware, only queue aware and basic cross layer schedule. From this figure it is evident that the combination of probabilistic user prioritization with cross layer aware strategy provides the better result over the alone aware schemes in the form of increased throughput, reduced delay and fair resource allocation.

5 Discussion

The performance analysis shows that the developed PCCS frame works well with several issues of the dense uplink NOMA small-cell networks. It can effectively adapt the channel variation and buffer status by applying the probabilistic scheduler, and transmit to the user that has good transmission opportunities without compromising the competitive service fairness. It causes better performance on throughput, spectral efficiency, and delay. With the combination of the channel information at the physical layer and queue status at MAC layer, cross-layer scheduling can optimize the resources utilization to get good queue stability and balanced QoS. By the help of urgent status to account for queue priority, and the delay performance with less packet congestion, also few packet losses with traffic at heavy load. Through the ablation analysis, the proposed system with probabilistic prioritization and cross layer scheduling combined gives better improvement than that only use single scheduler. And $O(NlogN)$ complex is also feasible for the number of active users in a practical system. Its performance shows great stability with more and more active users. Considering the requirement for massive connections and intelligent resource management and strict delay in 6G networks, the proposed system has a great potential to be a next generation scheduling scheme in the future wireless communications networks.

6 Conclusion

In this paper, a Probabilistic Channel-Aware Cross-Layer Scheduling (PCCS) frame is proposed for uplink NOMA communication in dense small-cell networks to tackle the issues of resource contention, channel variations and QoS assurance in highly loaded wireless environments. This frame integrates the physical layer channel information and the MAC layer queue information to make intelligent and adaptive scheduling and resource allocation decisions on the basis of probability-based user prioritization. Performance analysis shows that by utilizing both channel quality information and queue information the scheduling decision will be more efficient than those from traditional scheduling algorithms. Simulation results have shown that PCCS reaches a throughput 336.7 Mbps, a spectral efficiency of 16.84 bps/Hz, a fairness index of 0.94 and an average packet delay of 34.2 ms when there are 250 users under dense network. The throughput, spectral efficiency, fairness index and average packet delay achieved by PCCS outperform those obtained by the best-compared scheduler by about 27.4%, 22.1%, 6.8% and 22.8% respectively, which illustrates the advantage of this scheduling algorithm in balancing performance and resource utilization. Furthermore, it's observed from the ablation study that both probabilistic scheduling and cross-layer information can effectively contribute to the performance improvement. Both theoretically and practically, this paper successfully shows the power of joint use of random decision and cross-layer information for future NOMA scheduling in 6G wireless networks. The computation complexity is reasonable and adaptable to real-time implement in the dense wireless networks. It can further explore framework by incorporating AI-assisted scheduling algorithm, energy-aware resource allocation scheme, and multi-cell collaborative NOMA scheme in future works, especially for those arising 6G communication scenarios.

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