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Optimization of Power and Resource Allocation for 5G/6G Networks

Ph.D. Thesis Booklet

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1 Introduction

Cellular communication networks continue to advance rapidly, with current 5G deployments and the ongoing development of 6G concepts shaping the next generation of network capabilities. Driven by the explosive growth of the Internet of Things (IoT), cloud-based services, and real-time applications, these networks must provide not only higher data rates but also ultra-low latency, massive connectivity, and improved energy efficiency. This transformation is motivated by emerging applications such as autonomous vehicles, smart cities, industrial automation, and immersive extended reality, all of which demand unprecedented levels of performance and reliability.

To meet these emerging network requirements, researchers have focused on several key enabling technologies. One of these is Non-Orthogonal Multiple Access (NOMA), which allows multiple users to share the same spectrum resources through superposition coding and successive interference cancellation (SIC). This approach offers higher spectral efficiency and improved fairness compared to traditional orthogonal schemes, but it also introduces challenges related to power allocation, user grouping, and interference management [1, 2].

Another important technology is Device-to-Device (D2D) communication, which enables nearby devices to communicate directly without always relying on the base station. This capability reduces end-to-end latency, alleviates network congestion, and improves spectrum utilization. However, when D2D links operate alongside cellular users, interference becomes a critical issue, requiring advanced strategies for resource sharing, power control, and interference mitigation [7].

Beyond spectrum management, Mobile Edge Computing (MEC) brings computation closer to users, reducing latency and easing the energy demands on mobile devices, while Massive MIMO (mMIMO) enhances capacity and reliability through large antenna arrays. When integrated with technologies such as NOMA and D2D, these approaches also introduce new challenges related to task offloading decisions, channel allocation, power control, and overall resource optimization, particularly under mobility and rapidly varying channel conditions [6].

Taken together, these challenges point to a clear need for intelligent, adaptive resource management frameworks capable of unifying spectrum allocation, energy efficiency, and fairness in highly dynamic network conditions. By combining NOMA, D2D, MEC, and mMIMO, next-generation wireless systems can support the ever-growing demands of connected societies while ensuring sustainable performance. This dissertation builds upon these foundations to propose new models and algorithms that address the key issues of resource allocation, interference management, and energy efficiency in future mobile networks.

2 Research Objectives and Contributions

The evolution toward 5G and beyond networks introduces complex challenges in resource allocation, where high spectral efficiency, energy awareness, and adaptability to user mobility must be achieved simultaneously. This dissertation addresses these challenges by developing advanced models and algorithms that integrate Non-Orthogonal Multiple Access (NOMA), Mobile Edge Computing (MEC), Device-to-Device (D2D) communications, and machine learning (ML). The overarching goal is to deliver scalable, interference-aware, and energy-efficient resource allocation frameworks that support next-generation wireless applications.

The first objective focuses on improving spectral efficiency in NOMA-based systems through joint channel and power allocation. A two-stage strategy is developed in which users are first assigned to channels using a novel sorting-and-filling approach, followed by power allocation optimized through convex formulations and fractional power control. This enables non-orthogonal resource reuse under fairness constraints and advances existing allocation methods through improved efficiency and reduced complexity.

The second objective focuses on improving energy efficiency within Mobile Edge Computing (MEC) environments, where both local processing and offloaded computation contribute to overall energy demand. A comprehensive framework is introduced to model energy consumption during these two modes of operation. In NOMA uplink scenarios, optimized sub-channel and power control strategies are proposed to reduce transmission energy based on MEC processing requirements. In massive MIMO settings, scalable algorithms are designed to manage power for large user populations to support efficient task offloading. Together, these solutions enhance MEC energy efficiency under delay sensitivity and varying channel conditions, demonstrating significant energy savings across diverse network loads.

The third objective investigates spectrum reuse and fairness in D2D-enabled cellular systems. The research formulates the channel reuse problem as an optimization task and develops a heuristic solution that combines user clustering with graph-coloring techniques. Power control is integrated into this process to balance throughput gains with fairness requirements. Simulation results show that the proposed method effectively mitigates interference and enhances fairness in dense deployments, bridging theoretical optimization with scalable, real-world feasibility.

The final objective is to overcome the limitations of static allocation in dynamic mobility scenarios. A machine learning–based framework is developed that integrates mobility prediction with evolutionary multi-objective optimization. Using an enhanced Non-Dominated Sorting Genetic Algorithm II (NSGA-II), the approach jointly optimizes channel assignment, power control, and fairness under varying mobility profiles. Experimental evaluations confirm its superiority over conventional greedy and random strategies, while also opening pathways to future integration with deep reinforcement and federated learning.

Collectively, these objectives provide a unified set of contributions to resource allocation in heterogeneous 5G and beyond (5GB) networks. By combining optimization theory, heuristic methods, and machine learning, this dissertation advances both the theoretical foundations and the practical design of scalable, energy-aware, and mobility-adaptive wireless communication systems.

3 Research Methodology

This dissertation develops a multi-stage methodology to address the challenges of resource allocation in 5G and beyond networks. The approach integrates mathematical optimization, heuristic algorithms, and machine learning to design adaptive strategies that balance spectral efficiency, energy consumption, and fairness under dynamic conditions. The methodology combines theoretical modeling with simulation-driven validation, ensuring that the proposed solutions are both analytically sound and practically scalable.

The first phase concentrates on NOMA systems, where channel and power allocation are optimized to overcome the limitations of conventional orthogonal access. A heuristic channel assignment method is introduced and coupled with fractional power control, enabling non-orthogonal resource reuse while maintaining fairness and efficiency. The second phase extends to Mobile Edge Computing, modeling the trade-offs between local processing and task offloading. Energy-aware allocation strategies are proposed for both NOMA and massive MIMO environments, showing how network and device-level energy consumption can be reduced without sacrificing quality of service.

The third phase addresses spectrum reuse in D2D-enabled networks. Here, clustering and graph-coloring techniques are applied to manage interference and allocate channels effectively, with integrated power control ensuring balanced performance among users. The final phase incorporates user mobility by developing a predictive, machine learning–based framework. Leveraging evolutionary multi-objective optimization, the framework dynamically adapts channel assignment and power allocation to varying mobility profiles, demonstrating improved throughput, fairness, and spectral utilization.

The numerical results reported in this dissertation were obtained using custom-developed MATLAB and Python codes. The implementation was carried out using MATLAB together with standard toolboxes, including the Optimization Toolbox and Signal Processing Toolbox, as well as selected Python libraries for numerical computation, data processing, and visualization. The proposed algorithms and simulation scenarios were implemented directly based on the mathematical models and optimization formulations presented in the thesis, without relying on external network simulation frameworks.

Together, these phases form a coherent methodology that advances resource allocation research by uniting optimization, heuristics, and learning-based prediction. The results provide both theoretical insights and practical design strategies for scalable, energy-efficient, and mobility-aware wireless communication systems.

4 New Results

5 Thesis Group 1 [J1]

The first thesis group presents a novel and fully integrated framework for joint channel and power allocation in NOMA-based cellular systems, addressing limitations that existing OFDMA–NOMA approaches cannot overcome. The framework progresses from accurate system modeling and problem formulation to the design of the Channel User Sorting and Filling (CUSF) algorithm and an optimal iterative power allocation strategy. The novelty lies in splitting the resource allocation problem into two coordinated components. Firstly, I have introduced a novel algorithm and named it channel–user matching algorithm (CUSF). The CUSF algorithm shows stable, fair, and capacity-aware channel assignment. Secondly, I have integrated the CUSF with a two-stage power allocation method that combines water-filling with Fractional Transmit Power Control (FTPC) to achieve both inter- and intra-channel optimization. The novel contribution has shown significant improvements and was compared with other baseline algorithms.

Thesis 1.1 [J1]

I have developed a comprehensive downlink system model and formulated a joint optimization problem for NOMA-based cellular networks. This model captures both user-channel interactions and sub-channel multiplexing through a weighted sum-rate maximization framework that simultaneously considers fairness, power budget, and user grouping constraints. The formulation provides a general basis that reduces to OFDMA when the number of NOMA users per channel is set to one, demonstrating its flexibility and theoretical completeness.

Problem $P1$ formulates the joint channel and power allocation task in NOMA systems. The objective in (1a) maximizes the weighted sum-rate, where α_j controls user priority and R_{jn} represents the achievable rate of user u_j on subchannel c_n. Constraints (1b)–(1c) enforce global and per-subchannel power limits, while (1d)–(1e) ensure that each subchannel serves a bounded number of users through binary assignment variables x_{jn}. Finally, (1f) guarantees non-negative power allocation. This formulation captures the essential coupling between channel assignment and power allocation in NOMA, but the binary variables and interference-coupled rates make $P1$ a non-convex and NP-hard problem, motivating the decomposition and approximation strategies developed in the following sections.

$$
\begin{aligned}
P1 : \max_{x,p} \; & \sum_{u_j \in \mathcal{K}} \alpha_j \sum_{c_n \in \mathcal{N}} R_{jn} x_{jn} && \text{(1a)} \\
\text{s.t.} \quad & \sum_{u_j \in \mathcal{K}} \sum_{c_n \in \mathcal{N}} p_{jn} \leq P_T, && \text{(1b)} \\
& \sum_{u_j \in \mathcal{K}} p_{jn} \leq P_n, \quad \forall c_n \in \mathcal{N}, && \text{(1c)} \\
& s_\ell \leq \sum_{u_j \in \mathcal{K}} x_{jn} \leq S, \quad \forall c_n \in \mathcal{N}, && \text{(1d)} \\
& x_{jn} \in \{0, 1\}, && \text{(1e)} \\
& 0 \leq p_{jn}, \quad \forall u_j \in \mathcal{K},\; c_n \in \mathcal{N} && \text{(1f)}
\end{aligned}
$$

This unified formulation establishes the NP-hard nature of the problem and motivates the design of approximate but scalable algorithms for practical implementation [3].

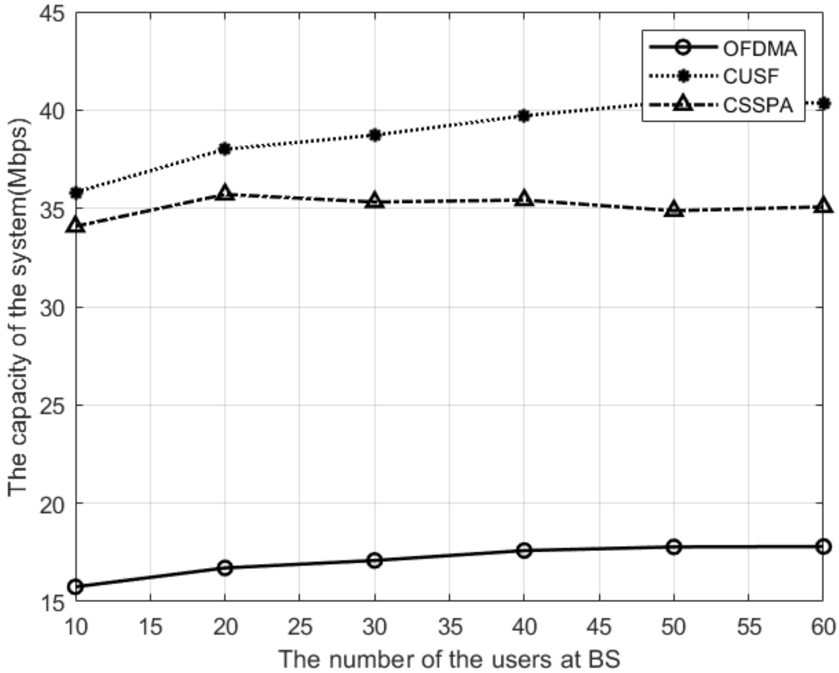

Figure 1: System capacity versus the number of users in a NOMA-based network.

Figure 1 shows that the proposed joint optimization framework increases capacity significantly with user density, establishing the foundation for subsequent algorithmic contributions.

Thesis 1.2 [J1]

I have designed a novel matching-based Channel User Sorting and Filling (CUSF) algorithm that achieves stable and fair sub-channel allocation in one-to-many NOMA systems. Because each sub-channel can accommodate only a limited number of users, an effective allocation method must compare different user groups and evaluate which matching configuration offers the best overall performance. To meet this requirement, I developed the Channel User Sorting and Filling (CUSF) algorithm, a tailored matching mechanism inspired by the structure of the National Intern Matching Program (NIMP), which is a centralized system that assigns medical interns to hospitals based on mutual preferences [5]. CUSF is adapted specifically to the constraints and objectives of NOMA resource allocation. This contribution introduces a systematic way for sub-channels and users to express preferences and form stable matches, enabling a controlled and fair multiuser assignment per sub-channel. Unlike conventional greedy methods, CUSF supports multiuser matching per sub-channel while ensuring fairness and stability.

CUSF extends matching theory to a one-to-many NOMA context, ensuring bilateral stability under multiuser quotas. The algorithm provably converges to a stable matching, as demonstrated by the included theorem and proof.

Results: Simulation results demonstrate that the CUSF algorithm delivers substantial and consistent capacity gains, achieving significant improvement (Shown in simulation results) over similar baseline algorithms and OFDMA. These benefits persist and even

Algorithm 1 Channel User Stable Fairness (CUSF) Algorithm

Require: Channel gain matrix between users $u_j \in \mathcal{K}$ and sub-channels $c_n \in \mathcal{N}$
Ensure: Stable and fair user–sub-channel assignment

```
Rank order both sub-channel and user lists based on channel gains as ζ and η
while there exist unassigned users requesting one-to-one matches do
    Assign all items marked as tentative
    Remove sub-channels with lower ranks from users already assigned
    Eliminate users (tentatively assigned) from sub-channels they ranked lower than
  their current assignment
end while
```

grow as the number of users increases, confirming the scalability and effectiveness of CUSF in dense multiuser NOMA scenarios.

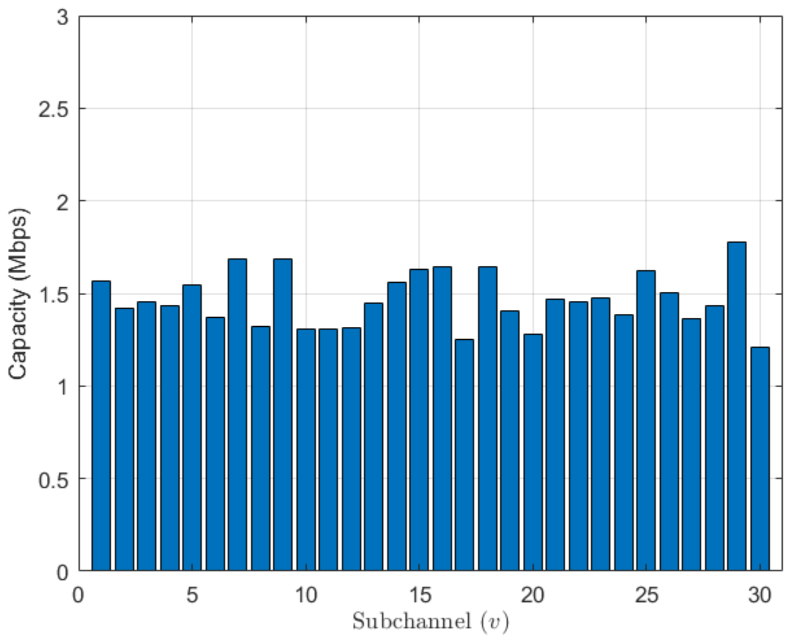

Figure 2: System capacity distribution over channels using the proposed CUSF algorithm.

CUSF achieves a balanced distribution of capacity across sub-channels, as illustrated in Fig. 2. Even under varying channel conditions the algorithm maintains fair throughput levels across all sub-channels, demonstrating fairness in terms of capacity. In addition to providing balanced performance, CUSF also achieves the highest overall system capacity among the NOMA algorithms studied.

Thesis 1.3 [J1]

I have proposed an iterative power allocation method that achieves the globally optimal inter-channel allocation through KKT-based water-filling, combined with FTPC for intra-channel power control in NOMA systems. This contribution separates the power allocation task into two stages: inter-channel (via KKT-based water-filling) and intra-channel (via FTPC). The Karush–Kuhn–Tucker (KKT) conditions provide a general framework for finding optimal solutions to constrained optimization problems. In our method, the KKT-based water-filling stage determines the optimal way to distribute power across channels by identifying a suitable power "level" that gives more power to stronger channels while respecting the total power limit. This ensures that the inter-channel allocation is both mathematically sound and computationally efficient before applying FTPC within each channel.

Algorithm 2 Iterative Power Allocation

Require: Initial value $\lambda_{(0)} > 0$, tolerance threshold ξ
Ensure: Optimal power allocations p_n and $p_{j,n}$

1: Set iteration index $i = 0$
2: **while** $|\lambda_{i+1} - \lambda_i| > \xi$ **do**
3: Compute inter-channel power:
4: $p_n = \frac{1}{\ln 2\,\lambda_i} - \frac{1}{H_n}$
5: Update the Lagrange multiplier:
6: $\lambda_{i+1} = \lambda_i - \mathcal{A}\left[P_T - \sum_{n\in\mathcal{N}} p_n\right]^+$
7: $i \leftarrow i + 1$
8: **end while**
9: Compute intra-channel NOMA power:
10: $p_{j,n} = \frac{p_n}{\sum_{u_i\in\mathcal{S}_n} H_{i,n}^{-\alpha_{\mathrm{FTPC}}}} H_{j,n}^{-\alpha_{\mathrm{FTPC}}}$

Results: As shown in Fig. 3, the proposed algorithm efficiently adapts to different alpha values. Lower alpha leads to higher overall system capacity. As alpha increases, more power is assigned to users with lower channel gains, improving fairness at the expense of slightly reduced capacity.

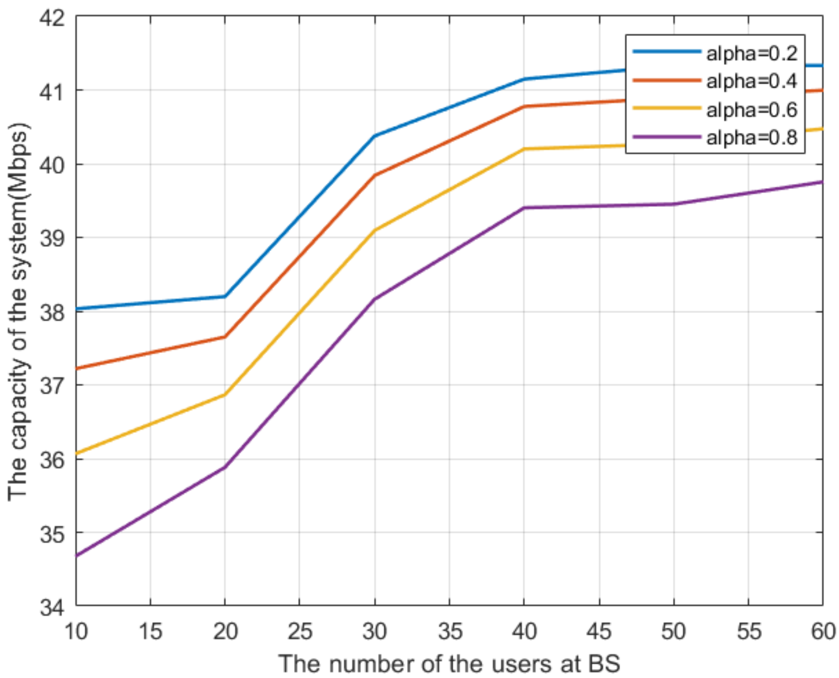

Figure 3: System capacity for different FTPC decay factors α_{FTPC}.

The two-stage strategy improves total power utilization while maintaining a controllable trade-off between capacity and fairness across multiplexed users. Combined with the CUSF channel allocation, this power allocation mechanism achieves a higher system capacity.

Summary of Thesis Group 1: The proposed framework introduces three major contributions: (i) a comprehensive joint optimization formulation for NOMA resource allocation, (ii) a stable and fair matching-based channel allocation algorithm (CUSF), and (iii) an optimal iterative power control mechanism combining water-filling and FTPC. Together, they significantly improve system capacity, fairness, and energy efficiency, confirming the novelty and technical depth of this research group.

6 Thesis Group 2 [J2]

This group presents my original contributions toward designing an integrated Mobile Edge Computing (MEC) framework optimized for energy efficiency and latency in NOMA and massive MIMO (mMIMO) systems. I proposed novel models, algorithms, and convex optimization methods that jointly address computation, communication, and scalability challenges. Each subthesis presents a distinct innovation that together forms a unified and practical MEC architecture for next-generation 5G/6G networks.

The pseudocode algorithms presented in this section are generalized forms that merge and abstract multiple algorithmic steps originally detailed in Chapter 3 Publication [J2]. They are rewritten here to emphasize conceptual integration and clarity, while all mathematical foundations and simulation results remain identical to the published version.

Thesis 2.1 [J2]

I have developed a unified DVS-based local-processing framework for energy optimization under both deterministic and stochastic workloads. I also derived closed-form energy expressions to capture the delay–energy trade-off. This thesis investigates the energy consumption incurred by a user when executing computational tasks locally. I developed a unified analytical local-processing framework based on Dynamic Voltage Scaling (DVS), where the processor supply voltage is adjusted by the system so that the CPU clock frequency can be selected according to the workload and delay requirement, thereby reducing energy consumption compared to running at unnecessarily high speed [8]. The framework treats two practical operating regimes: (i) deterministic workloads that must satisfy deadline constraints and (ii) stochastic workloads that require only statistical delay guarantees. I derived closed-form energy expressions for both regimes, which enables direct quantification of the computation time–energy trade-off and supports energy-aware decisions between local execution and offloading.

Thesis 2.1.1 – Tasks with Known Working Load For tasks with known computational workload, each CPU cycle requires a specific processing frequency, and the task must be completed within a predefined deadline. Let W_k denote the total number of CPU cycles required by task k, $f_{k,i}$ the CPU frequency allocated to the i-th cycle of task k, and T_k^D the maximum allowable execution delay (deadline). The execution time constraint is expressed as

$$\sum_{i=1}^{W_k} \frac{1}{f_{k,i}} \leq T_k^D. \tag{2}$$

Assuming a fixed CPU frequency f_k across all execution cycles, the above constraint reduces to

$$\frac{W_k}{f_k} \leq T_k^D, \tag{3}$$

$$f_k \geq \frac{W_k}{T_k^D}. \tag{4}$$

Using the adopted local computation energy model, where τ denotes the effective switched capacitance of the processor, I derived the minimum achievable local computation energy for task k by enforcing the lower bound on the CPU frequency. The resulting minimum energy consumption is given in closed form as

$$E_{k_{\min}}^c = \frac{\tau (W_k)^3}{(T_k^D)^2}, \tag{5}$$

where $E_{k_{\min}}^c$ represents the minimum local execution energy. This expression characterizes the optimal constant-frequency operating point under DVFS that minimizes local computation energy while satisfying the deadline constraint.

Thesis 2.1.2 – Tasks with Unknown Working Load For tasks with unknown computational demand, soft real-time requirements are considered, where only statistical performance guarantees are required. I modeled the total workload of task k as

$$W_k = D_k \widehat{C_k}, \tag{6}$$

where D_k denotes the task input data size and $\widehat{C_k}$ is a random variable representing the required number of CPU cycles per data unit, drawn from a known probability distribution.

Let $F(w)$ denote the cumulative distribution function (CDF) of the workload, defined as

$$F(w) = \mathbb{P}[W \leq w], \tag{7}$$

and let the complementary cumulative distribution function (CCDF) be $F^c(w) = 1 - F(w)$.

To minimize the expected local computation energy while satisfying a statistical deadline constraint T^D, I formulated the following optimization problem:

$$P_2 : \quad \min_{f(w)} \sum_{w=1}^{W} \tau F^c(w) \, [f(w)]^2 \tag{8a}$$

$$\text{s.t.} \quad \sum_{w=1}^{W} \frac{1}{f(w)} \leq T^D, \tag{8b}$$

$$f(w) \geq 0, \tag{8c}$$

where $f(w)$ denotes the CPU frequency selected when the workload realization equals w.

I solved this constrained problem using Karush–Kuhn–Tucker (KKT) conditions and obtained a closed-form expression for the minimum expected energy consumption, denoted by E^s, as

$$E^s = \frac{\tau}{(T^D)^2} \left[\sum_{w=1}^{W} \left(F^c(w) \right)^{1/3} \right]^3 . \tag{9}$$

To obtain a tractable analytical expression for the workload distribution, I adopted a normal distribution as an acceptable approximation. Let μ and σ denote the mean and standard deviation of the workload distribution, respectively. The CCDF can then be expressed as

$$F^c(w) = \frac{1}{2} - \frac{1}{2} \mathrm{erf} \left(\frac{w - \mu}{\sigma \sqrt{2}} \right), \tag{10}$$

where $\mathrm{erf}(\cdot)$ denotes the Gaussian error function.

Finally, I applied a confidence-based criterion to determine the maximum workload W such that the statistical deadline requirement is satisfied with probability δ, where δ is a confidence level close to one. The resulting workload bound is given by

$$W = \mu + \sigma \sqrt{2}\, \mathrm{erf}^{-1}(2\delta - 1), \tag{11}$$

where $\mathrm{erf}^{-1}(\cdot)$ denotes the inverse error function.

As shown in Fig. 4, local-processing energy under DVFS exhibits a clear delay–energy trade-off: as the allowable execution delay increases, the minimum required operating frequency decreases, resulting in lower computation energy, whereas stricter delay constraints increase the energy demand. The figure also confirms the monotonic increase of energy with task input size due to the corresponding growth in computational workload. Finally, I evaluated the aggregated local energy for different numbers of users to quantify the network-level energy impact in multi-user operation.

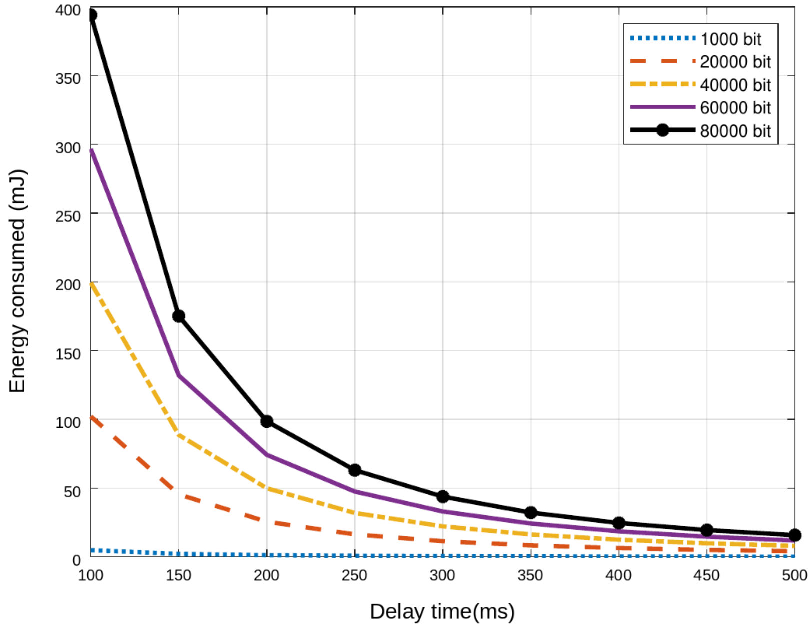

Figure 4: Local energy consumption for different delay times.

Thesis 2.2

I have developed a modified many-to-one Gale–Shapley matching algorithm for uplink NOMA channel assignment. The proposed SMUSC method achieves stable and optimal channel–user matching with improved system capacity. This sub-thesis addresses the uplink channel-assignment of the data-offloading stage. After formulating the overall mixed-integer problem $P1$, I reduced its combinatorial complexity by focusing on the user–sub-channel matching structure and by adopting a heuristic assignment mechanism. I present the NOMA configuration, where I modified the Gale–Shapely marriage algorithm to operate in a many-to-one manner consistent with NOMA clustering. The base station is assumed to centrally control the matching process.

Preference Lists and Ordering Rule Let $\mathcal{K}$ and $\mathcal{N}$ denote two disjoint and finite sets of users and sub-channels, respectively. Each user has a preference ordering over sub-channels, and each sub-channel has a preference ordering over users, where channel gain is used as the decision factor. Preferences are assumed transitive. The ordered preference lists are written as

$$O(u_k) = \{n_i, n_j, u_k, n_l, \ldots\}, \tag{12}$$
$$O(n_k) = \{u_i, u_j, n_k, u_l, \ldots\}. \tag{13}$$

The inclusion of u_k in $O(u_k)$ indicates that all sub-channels appearing after u_k are considered unacceptable due to insufficient channel gain; similarly, the inclusion of n_k in $O(n_k)$ indicates that users appearing after n_k are unacceptable for sub-channel n_k.

The preference relations are denoted as $n_i \succeq_{u_k} n_j$, meaning that user u_k prefers n_i at least as much as n_j, and $u_k \preceq_{n_i} u_l$, meaning that sub-channel n_i prefers u_k at most as much as u_l.

Many-to-One Matching Structure Each user can be matched to at most one sub-channel, while each sub-channel can be matched to multiple users (S) dictated by channel conditions and NOMA complexity. Let $\mu_p(\cdot)$ denote the matching function. The matching satisfies:

1. $|\mu_p(u_k)| = 1$, $\forall u_k \in \mathcal{K}$.
2. $|\mu_p(n_i)| = S$, $\forall n_i \in \mathcal{N}$. If the number of acceptable users is less than S, the remaining positions are filled by n_i.
3. $|\mu_p(u_k)| = n_i \iff |\mu_p(n_i)| = u_k$.

Modified Gale–Shapley Procedure (Many-to-One) The modified procedure operates iteratively. Each unassigned user proposes to its most preferred sub-channel that has not yet rejected it. Upon receiving proposals, a sub-channel tentatively accepts users according to its preference ordering (based on channel gains), subject to its capacity S. If the sub-channel is full and receives a more preferred proposal, it replaces its least preferred currently accepted user. This process repeats until all users are assigned (or exhaust their acceptable lists). The resulting matching is then used as the channel assignment for the NOMA uplink offloading stage. I have also proved that this matching algorithm is stable and leads to optimum channel-user assignmnet.

Algorithm 3 Stable Matching of Users to Sub-channels (SMUSC)

Input:
    $O(u_k)$: users' preference lists over sub-channels
    $O(n_i)$: sub-channels' preference lists over users
Output: Stable matching μ_p
Step 1: Initialization
for each user $u_k \in \mathcal{K}$ **do**
    $\mu_p(u_k) \leftarrow \emptyset$ ▷ unassigned
end for
for each sub-channel $n_i \in \mathcal{N}$ **do**
    $\mu_p(n_i) \leftarrow \{n_i, \ldots, n_i\}$ ▷ S empty slots
end for
Step 2: Proposal Loop
while there exists a user u_k with $\mu_p(u_k) = \emptyset$ and $O(u_k) \neq \emptyset$ **do**
    Choose such a user u_k
    u_k proposes to its most preferred sub-channel $n_i \in O(u_k)$
    Remove n_i from $O(u_k)$
    if n_i has an available slot in $\mu_p(n_i)$ **then**
        Tentatively accept u_k into $\mu_p(n_i)$ and set $\mu_p(u_k) \leftarrow n_i$
    else
        Let u_ℓ be the least preferred user currently in $\mu_p(n_i)$
        if n_i prefers u_k over u_ℓ **then**
            Replace u_ℓ with u_k in $\mu_p(n_i)$
            Set $\mu_p(u_k) \leftarrow n_i$ and $\mu_p(u_\ell) \leftarrow \emptyset$
        end if
    end if
end while
Step 3: Finalization
return μ_p

Symbols $\mathcal{K}$: set of users; $\mathcal{N}$: set of sub-channels; u_k: user index k; n_i: sub-channel index i; S: maximum number of users multiplexed on one sub-channel; $O(u_k)$: user u_k preference list over $\mathcal{N}$; $O(n_i)$: sub-channel n_i preference list over $\mathcal{K}$; $\succeq_{u_k}$: user-side preference relation; $\preceq_{n_i}$: channel-side preference relation; $\mu_p(\cdot)$: matching function mapping users and sub-channels to their assigned partners.

As shown in Fig. 5, implementing the NOMA algorithm has significantly increased system capacity. For this purpose, I have fixed each mobile output power to 20 dBm for both OFDMA and NOMA users.

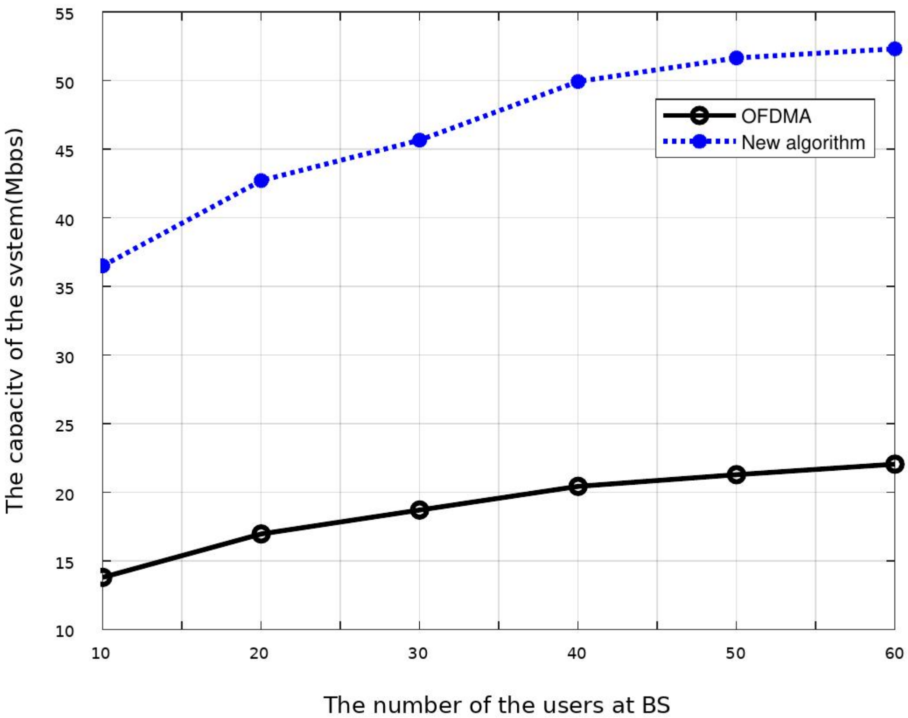

Figure 5: Capacity of the system versus different numbers of users.

Thesis 2.3 [J2]

I have developed a structured and energy-aware NOMA uplink power allocation method based on the user clustering outcome. Building on the constraints already established in problem $P1$, I formulated the joint power–resource optimization problem $P3$ to minimize the overall remote energy consumption while guaranteeing strict delay-driven rate constraints and per-user power limits. Specifically, I minimized the sum remote energy $\sum_{k\in\mathcal{K}} E_k^r$ subject to the minimum rate requirement $R_k \geq \frac{D_k}{T_k^D - T_k^c}$, the maximum transmit power constraint $\sum_{n\in\mathcal{N}} p_{kn} \leq P_k^{\max}$, and non-negativity of the allocated powers. In this formulation, the achievable uplink NOMA rate is expressed as

$$R_k = \log_2\left(1 + \frac{p_k g_k}{\sum_{i=1}^{j-1} p_i g_k + \sigma_n^2}\right), \tag{14}$$

and the remote energy term is given by

$$E_k^r = \frac{p_k D_k}{R_k}, \tag{15}$$

which explicitly couples energy, rate, and transmit power in a fractional form.

I have reduced the complexity of $P3$ by isolating the power optimization structure. Although the channels are non-interfering, the shared resources make the power allocation interdependent and the overall problem difficult to solve directly. I simplified the objective and obtained the equivalent power-minimization problem which i named $P4$.

I have transformed the non-convex rate constraint into a convex form using a tight lower bound and logarithmic variable substitution.

The rate constraint in $P4$ is non-convex because it depends on the SINR expression. To make the problem convex, two key steps are applied. First, I benefited from logarthemic function to simplify the problem. Second, the non-convex term $\log(1 + \mathrm{SINR})$ is replaced by a tight lower-bound approximation that is constructed at a chosen operating SINR point; then, a log-domain reformulation of the power variables is used so the resulting constraint takes a convex form (based on the convexity of the log-sum-exp structure). Together, these two steps convert the original non-convex rate constraint into a convex surrogate that can be solved efficiently.

I have finally reformulated the power allocation as a convex optimization problem and derived the optimal solution using KKT conditions. Using the above convexification, I obtained the convex problem $P5$:

$$P5: \min_{\widehat{p}} \sum_{k \in \mathcal{K}} e^{\widehat{p}_k} \tag{16}$$

$$\text{s.t. } \widehat{R}_k \geq \frac{\nu D_k}{T_k^D - T_k^c}, \ \forall k \in \mathcal{K}, \tag{17}$$

$$\sum_{n \in \mathcal{N}} e^{\widehat{p}_k} \leq \widehat{P_k^{\max}}, \ \forall k \in \mathcal{K}, \tag{18}$$

I then analytically solved the problem $P5$ to obtain the optimal uplink power allocation. The iterative solution steps are summarized in Algorithm 4. This achievement provided an efficient method to compute the optimal NOMA uplink powers.

Algorithm 4 Power Allocation

Input:
P_k: Power levels
D_k: Data demands
T_k^D: Delay tolerance
T_k^c: Channel conditions
Output: Power allocation for each user p_k
Step 1: Initialization
Set initial conditions:
$z_0 \gg 1 \rightarrow \{\zeta_k = 1, \gamma_k = 0\}$
Initialize Lagrange multipliers λ_k, μ_k
Set iteration index $i = 1$
Set convergence threshold δ
Step 2: Iterative Optimization
repeat
Compute gradients for λ_k and μ_k (See equations in Appendix B, B-9 and B-10)
Update Lagrange multipliers:

$$\lambda_k^{(i+1)} = \left[\lambda_k^{(i)} - \eta_\lambda \cdot \text{Grad}_{\lambda_k}\right]^+$$

$$\mu_k^{(i+1)} = \left[\mu_k^{(i)} + \eta_\mu \cdot \text{Grad}_{\mu_k}\right]^+$$

Update power value:

$$\widehat{p}_k = \log\left(\frac{\mu_k \zeta}{\lambda_k + 1}\right)$$

Check for convergence:
Ensure primal and dual feasibility conditions
Check complementary slackness
Increment iteration index $i \leftarrow i + 1$
until convergence criteria are met
Step 3: Final Power Update
Set actual power:

$$p_k = e^{\widehat{p}_k}$$

Update $\{\zeta_k, \gamma_k\}$
End Procedure

Finally, I linked the optimized NOMA power allocation to computation resource provisioning. After obtaining the optimal transmit power values from Algorithm 4, I derived the remaining computation resource lower bound:

$$q_j \geq \frac{W_j}{c\left(T_j^D - \frac{D_j}{R_j}\right)}, \tag{19}$$

where R_j follows the SINR-based NOMA rate expression using the optimized p_j. This final step enables computation resources to be assigned according to availability while maximizing the processing margin for each device.

As shown in Fig. 6, the energy is computed according to (15), we notice that it increases with different numbers of users, and the decrease in delay requirement causes a significant increase in energy required.

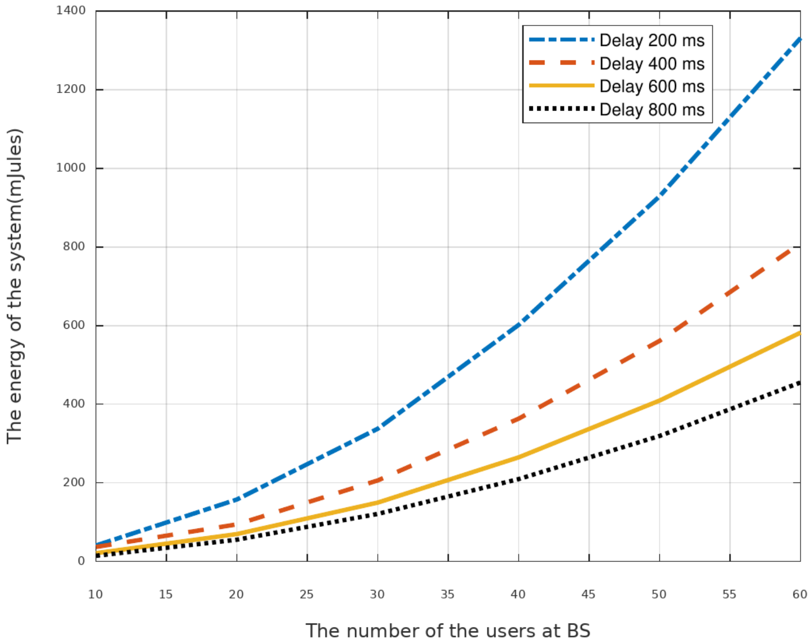

Figure 6: Energy consumed for remote processing Vs. number of users.

Thesis 2.4 [J2]

I have developed a clustering-aware power-allocation framework for mMIMO uplink systems using CCCP-based convex optimization. I also integrated K-means clustering and inter-cluster coordination to enable scalable power control under QoS constraints. In this thesis, I developed a clustering-aware power-allocation framework for mMIMO uplink systems, where the base station exploits spatial multiplexing through beamforming under channel hardening and favorable channel conditions [4]. I considered a base station that employs a large antenna array (M antennas) arranged as a Uniform Linear Array (ULA). I modeled the mMIMO uplink by first defining the ULA array response as an angle-dependent steering vector, where each antenna element experiences a phase shift determined by the AoA and array geometry. Then, I expressed each user channel as a superposition of multiple multipath components (plane waves) arriving from different angles. Based on this construction, I defined the spatial correlation matrix as the expected outer product of the array responses, which captures how channel energy is correlated across antennas. Finally, I derived a per-entry expression of the correlation matrix by averaging over the multipath gains and integrating over the AoA distribution.

For the uplink, the received signal is

$$\boldsymbol{y} = \sum_{k=1}^{K} \mathbf{h}_k s_k + \mathbf{n}, \tag{20}$$

and signal detection for user k is performed by correlating $\boldsymbol{y}$ with a beamforming vector:

$$\boldsymbol{w}_k^H \boldsymbol{y} = \sum_{k=1}^{K} \boldsymbol{w}_k^H \boldsymbol{h}_k s_k + \mathbf{n}. \tag{21}$$

This yields the SINR expression

$$\mathrm{SINR}_k = \frac{p_k \left|\mathbf{w}_k^H \mathbf{h}_k\right|^2}{\sum_{j \neq k} p_j \left|\mathbf{w}_k^H \mathbf{h}_j\right|^2 + \sigma^2 \|\mathbf{w}_k\|^2}. \tag{22}$$

Assuming estimated channels $\hat{\mathbf{h}}_{\mathbf{k}}$ at the base station, the estimated channel matrix is

$$\hat{\mathbf{H}} = [\hat{\mathbf{h}}_{\mathbf{1}},\ \hat{\mathbf{h}}_{\mathbf{2}},\ ...,\ \ \hat{\mathbf{h}}_{\mathbf{K}}], \tag{23}$$

and with zero-forcing combining:

$$\mathbf{W} = \hat{\mathbf{H}}(\hat{\mathbf{H}}^H \hat{\mathbf{H}})^{-1}. \tag{24}$$

Based on these expressions, I formulated the uplink power-control problem as

$$P6 : \min \sum_{k \in \mathcal{K}} p_k \tag{25a}$$

$$\text{s.t. } \theta \leq \frac{R_k}{R_k^{\min}} \tag{25b}$$

$$0 \leq p_k \leq P^{\max} \tag{25c}$$

where the achievable rate and the minimum-rate requirement are given by

$$R_k = \log_2 \left(1 + \frac{p_k \left|\mathbf{w}_k^H \mathbf{h}_k\right|^2}{\sum_{j \neq k} p_j \left|\mathbf{w}_k^H \mathbf{h}_j\right|^2 + \sigma^2 \|\mathbf{w}_k\|^2} \right) \tag{26}$$

$$R_k^{\min} = \frac{D_k}{T_k^D - T_k^c}. \tag{27}$$

The fairness parameter θ controls the operating point, where $\theta \geq 1$, and $\theta = 1$ guarantees the minimum rate. Since the SINR-coupled constraint makes $P6$ non-convex, I solved it using CCCP by rewriting the rate into a DC form:

$$R_k = \log_2 \left(1 + \sum_j p_j \left|\mathbf{w}_k^H \mathbf{h}_j\right|^2 + \sigma^2 \|\mathbf{w}_k\|^2 \right) -$$

$$\log_2 \left(1 + \sum_{j \neq k} p_j \left|\mathbf{w}_k^H \mathbf{h}_j\right|^2 + \sigma^2 \|\mathbf{w}_k\|^2 \right) \tag{28}$$

$$= f_1(\boldsymbol{p}) - f_2(\boldsymbol{p}). \tag{29}$$

Then, I linearized the second term using Taylor expansion:

$$f_2(\boldsymbol{p}) = f_2(\boldsymbol{p}^{(t)}) + (\boldsymbol{p} - \boldsymbol{p}^{(t)})^T \nabla f_2(\boldsymbol{p}^{(t)}), \tag{30}$$

with gradient

$$\nabla f_2(p^{(t)}) = \frac{1}{\ln(2)} \cdot \frac{\left|\mathbf{w}_k^H \mathbf{h}_j\right|^2}{\sum_{j\neq k} p_j^{(t)} \left|\mathbf{w}_k^H \mathbf{h}_j\right|^2 + \sigma^2 \|\mathbf{w}_k\|^2}. \tag{31}$$

This procedure transforms $P6$ into a sequence of convex subproblems solvable by standard convex optimization tools. However, for large user populations, direct CCCP can still be computationally expensive, which motivated my clustering contribution described next.

Thesis 2.4.1 – User Clustering for Complexity Reduction

To reduce the complexity in dense mMIMO systems, I proposed to cluster users before applying CCCP. I applied K-means clustering based on channel gain to partition users into N_{clusters} groups prior to optimization.

Algorithm 5 K-means Clustering Based on Channel Gain

Input:
  K: Number of users
  $\mathbf{h}_k$ for $k = 1, 2, \ldots, K$: Channel vectors
  N_{clusters}: Number of clusters
  $T_{\max}$: Maximum number of iterations
  ϵ: Convergence threshold
Output:
  Cluster assignments $\mathcal{C}_i$ for each user k
  Cluster centers $\boldsymbol{\mu}_i$
Step 1: Compute Channel Gains
Compute channel gain for each user: $g_k = \|\mathbf{h}_k\| \quad$ for each user k
Step 2: Initialize Cluster Centers
Randomly initialize N_{clusters} cluster centers $\boldsymbol{\mu}_i$ from $\{g_k\}$
Step 3: Repeat Until Convergence or $T_{\max}$ Iterations
for each iteration $t = 1$ to $T_{\max}$ **do**
  Assignment Step
  Assign each user k to the nearest cluster center:

$$\mathcal{C}_i = \left\{ k \mid \min_j |g_k - \boldsymbol{\mu}_j| \right\}$$

  Update Step
  Update the cluster centers:

$$\boldsymbol{\mu}_i = \frac{1}{|\mathcal{C}_i|} \sum_{k \in \mathcal{C}_i} g_k \quad \text{for each cluster } i$$

  Convergence Check
  if $\max_i |\boldsymbol{\mu}_i^{(t)} - \boldsymbol{\mu}_i^{(t-1)}| < \epsilon$ **then**
    Break loop
  end if
end for
Step 4: Output Final Clusters
return final cluster assignments $\mathcal{C}_i$ and centers $\boldsymbol{\mu}_i$

After clustering, the original large-scale optimization is decomposed into smaller subproblems defined on each cluster, enabling scalable processing in high-K scenarios.

Thesis 2.4.2 – CCCP Power Optimization with Inter-Cluster Coordination

After forming clusters, I applied CCCP within each cluster to compute the intra-cluster power allocation while satisfying the SINR-based QoS constraints. To manage inter-cluster interference, I then coordinated the clusters by treating each cluster as an aggregated entity and applying power scaling factors based on its interference contribution to other clusters.

Algorithm 6 Power Allocation in mMIMO Uplink using K-means Clustering and CCCP

Input:
  K: Number of users
  $\mathbf{h}_k$ for $k = 1, 2, \ldots, K$: Channel vectors
  $P_k^{\max}$: Maximum power for each user
  $R_k^{\min}$: Minimum rate for each user
  N_{clusters}: Number of clusters
  $T_{\max}$: Maximum number of CCCP iterations
  ϵ: Convergence tolerance
  β: Scaling factor parameter
Output: Optimized power allocation p_k for each user k
Step 1: K-means Clustering
Perform K-means clustering to group users based on their channel vectors
Step 2: Intra-Cluster Power Allocation (CCCP)
for each cluster $\mathcal{C}_i$ **do**
  Initialize power values $p_k^{(0)}$ for all $k \in \mathcal{C}_i$
  for iteration $t = 1$ to $T_{\max}$ **do**
    Linearize the non-convex part of the SINR constraints
    Solve the convex subproblem to update power values $p_k^{(t+1)}$
    if $\|p_k^{(t+1)} - p_k^{(t)}\| < \epsilon$ **then**
      Stop the iteration
    end if
  end for
end for
Step 3: Inter-Cluster Coordination
for each cluster $\mathcal{C}_i$ **do**
  Calculate inter-cluster interference I_{ij} for all clusters
  Determine scaling factor:
$$\alpha_i = \frac{1}{1 + \beta \cdot I_{i,\text{total}}}$$
  Apply the scaling factor to each user $k \in \mathcal{C}_i$:
$$p_k \leftarrow \alpha_i \cdot p_k$$
end for
Step 4: Finalization
Output the final optimized power allocations p_k for all users

Finally, once the transmit powers are obtained, I applied the optimal resource allocation equations (which I derived before for the NOMA) to allocate computation resources consistently with the delay constraints.

Thesis 2.5 [J2]

I have developed a lower-complexity power allocation approach by reformulating the original problem into a simplified SINR-based model. I also applied a bisection-based IPSBA method to efficiently find suitable power scaling values while preserving energy efficiency and QoS performance. The power allocation algorithm shows high complexity. For this purpose, I introduced a less strict approach to reduce the complexity, as demonstrated by the following problem:

$$P7 : \min \alpha \tag{32a}$$

s.t.

$$\gamma \left(\sum_j p_j \left| \mathbf{w}_k^H \mathbf{h}_j \right|^2 + \sigma^2 \|\mathbf{w}_k\|^2 \right) \leq p_k \left| \mathbf{w}_k^H \mathbf{h}_k \right|^2 \tag{32b}$$

$$0 \leq p_k \leq \alpha P^{\max} \tag{32c}$$

In $P7$, I have solely considered the SINR within the log, considering an increase in this term equivalent to an increase in the log itself. The challenge in the new problem is to find the best γ and then solve the problem. For this purpose, I have implemented the well-known bisection algorithm to find an acceptable value for γ without compromising energy consumption. This can be controlled by carefully selecting the range for γ, then applying bisection until finding the best value. The IPSBA algorithm illustrates the steps to solve $P7$.

Algorithm 7 Iterative Power Scaling Bisection Algorithm (IPSBA)

Input:
Maximum uplink power $P^{\max}$
Precision level ϵ
Output:
Optimal SINR threshold γ_{opt}
Scaling factor α_{opt}
Power allocations $\{p_k^{\text{opt}}\}$

Step 1: Initialization
Set $\gamma_{\text{lower}} \leftarrow \gamma_{\min}$
Set $\gamma_{\text{upper}} \leftarrow \min_k \left(\frac{P^{\max} |\mathbf{w}_k^H \mathbf{h}_k|^2}{\sigma^2 \|\mathbf{w}_k\|^2} \right)$
Initialize $\rho_{jk}^{\text{opt}} \leftarrow 0$ for all k
Step 2: Bisection Iteration
while $\gamma_{\text{upper}} - \gamma_{\text{lower}} > \epsilon$ **do**
    Compute midpoint:
$$\gamma_{\text{mid}} = \frac{\gamma_{\text{lower}} + \gamma_{\text{upper}}}{2}$$
    Solve problem $P3.7$ using γ_{mid}
    if feasible solution found **then**
        Set $\gamma_{\text{lower}} \leftarrow \gamma_{\text{mid}}$
        Update p_k^{opt} and α_{opt}
    else
        Set $\gamma_{\text{upper}} \leftarrow \gamma_{\text{mid}}$
    end if
end while
Step 3: Finalization
return Final power allocations $\{p_k^{\text{opt}}\}$, SINR threshold γ_{opt}, and scaling factor α_{opt}

Fig. 7, shows the impact of increasing antenna number on total SE in the cell. The figure shows that SE increases proportionally with antenna numbers, as evidenced by the equal power distributions. However, we observe that the rate does not significantly increase due to the application of optimisation algorithms. This is because we have set the minimum rate, which positively impacts energy consumption as the number of antennas increases.

Finally, once the transmit powers are obtained, I applied the optimal resource allocation equations (which I derived) to allocate computation resources consistently with the delay constraints.

7 Thesis Group 3 [J3+C1]

This group presents my original contributions toward resource allocation in D2D-enabled cellular networks under both static and mobility-driven conditions. This group presents my contributions on resource allocation for D2D-enabled cellular networks, focusing on efficient spectrum reuse under interference and user mobility. I developed (i) an optimization-based channel reuse formulation that is transformed into an ILP and supported by scalable heuristics using K-means clustering and graph coloring, and (ii) a mobility-aware framework that integrates zone-based mobility prediction with multi-objective NSGA-II to jointly optimize power control and channel assignment while balancing throughput, inter-

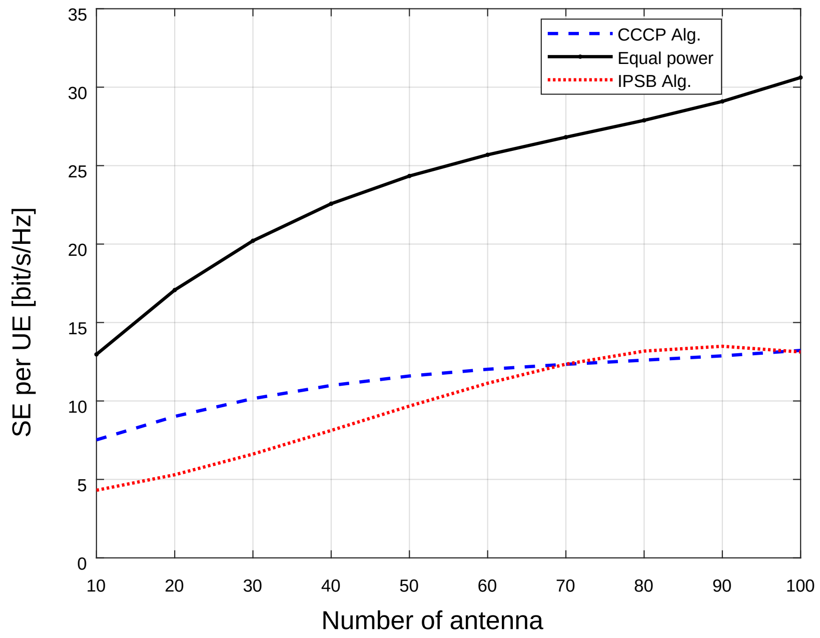

Figure 7: Spectral Efficiency Vs Number of Antenna.

ference, and fairness. Simulation results confirm improved network performance compared to static and heuristic baselines.

The pseudocode algorithms presented in this section are generalized forms that merge and abstract multiple algorithmic steps originally detailed in Chapter 4 and 5 and related publications. They are rewritten here to emphasize conceptual integration and clarity, while all mathematical foundations and simulation results remain identical to the published versions.

Thesis 3.1 [C1]

I have developed a scalable two-stage channel reuse framework for D2D-underlay cellular networks using K-means clustering and conflict-graph coloring. The proposed approach reduces assignment complexity and mitigates cross-tier and co-tier interference. In this subthesis, I addressed the channel reuse challenge in D2D-underlay cellular networks by proposing a scalable two-stage solution that avoids directly solving the integer channel assignment problem in large deployments. Starting from the interference structure of the reuse scenario and the binary channel-assignment formulation, I solved the problem using two main steps: (i) proximity-based user clustering using K-means, and (ii) interference-aware subchannel allocation using conflict-graph coloring. This two-stage design reduces the search space, improves scalability, and enables practical reuse decisions that mitigate the three dominant interference mechanisms (D2D→BS, CU→D2D, and D2D→D2D).

Step 1 — Proximity-based user clustering using K-means

To make the reuse problem tractable in dense networks, I first grouped the overall user set $u_j \in \mathcal{K}$ (including $\mathcal{U}_{\mathrm{CU}}$ and $\mathcal{U}_{\mathrm{D2D}}$) into k clusters according to proximity to the BS.

I applied the K-means algorithm, where each cluster is represented by a centroid c_i and users are assigned to their nearest centroid. The clustering objective minimizes the within-cluster variance as given in the original text:

$$J(C) = \sum_{i=1}^{k} \sum_{u_j \in \mathcal{L}_i} \|u_j - c_i\|^2,$$

where $\mathcal{L}_i$ is the set of users assigned to cluster i. The K-means procedure follows the iterative steps (initialization, assignment, centroid update, and repetition) and yields geographically coherent user groups. This stage reduces the effective complexity of the reuse problem by constraining subsequent channel decisions to structured local regions rather than the full network.

Step 2 — Interference-aware reuse assignment via conflict-graph coloring

After clustering, I modeled reuse conflicts using a graph representation and applied graph coloring to allocate subchannels while minimizing interference. Specifically, I constructed the auxiliary conflict graph $\hat{G}(\hat{V}, \hat{E})$, where each vertex $\hat{v}_j \in \hat{V}$ represents an active user and an edge $\hat{e} \in \hat{E}$ connects $\hat{v}_j$ and $\hat{v}_m$ when their chosen subchannels overlap. *Proper* spectrum allocation corresponds to a proper coloring of $\hat{G}$, where each color maps to a unique subchannel $c_n \in \mathcal{N}$. Consequently, the minimum number of colors required to avoid co-channel conflicts is characterized by the chromatic number $\chi(\hat{G})$.

To validate the proposed two-stage solution (K-means clustering followed by conflict-graph coloring), I evaluated the resulting channel reuse pattern and its interference/fairness behavior using the following figures.

Channel distribution after graph coloring. Fig. 8 presents the final channel distribution obtained after applying graph coloring. Different colors indicate distinct channels, confirming that the coloring step produces a structured allocation across the clustered users.

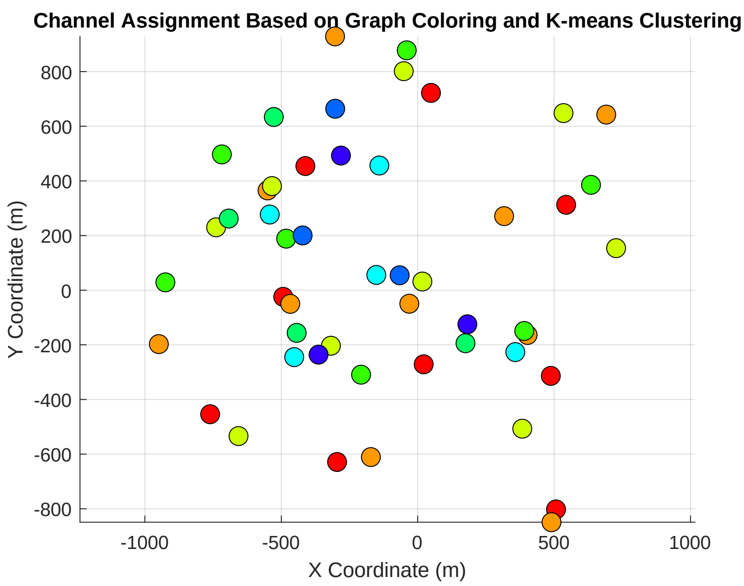

Figure 8: Channel distribution after applying graph coloring.

Per-channel load and utilization. To assess channel utilization and the balance of assigned users, Fig. 9 shows the number of users allocated to each channel. This visualization highlights how the reuse assignment distributes users across channels, which directly reflects the achieved load balance in the proposed allocation.

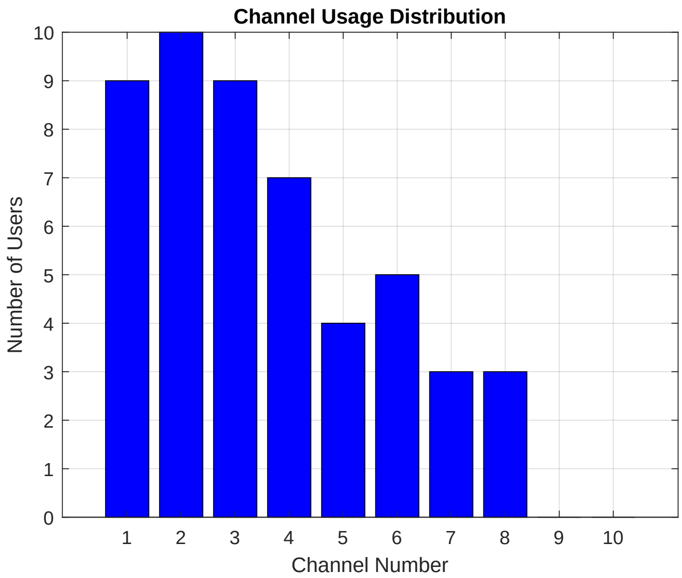

Figure 9: Users per channel after allocation.

Interference evaluation under the reuse allocation. Fig. 10 evaluates the effectiveness of the channel assignment by measuring the interference level experienced by each user. In this figure, interference is quantified as the number of neighbors that use the same channel, which reflects the quality of the conflict-graph coloring outcome in reducing co-channel conflicts.

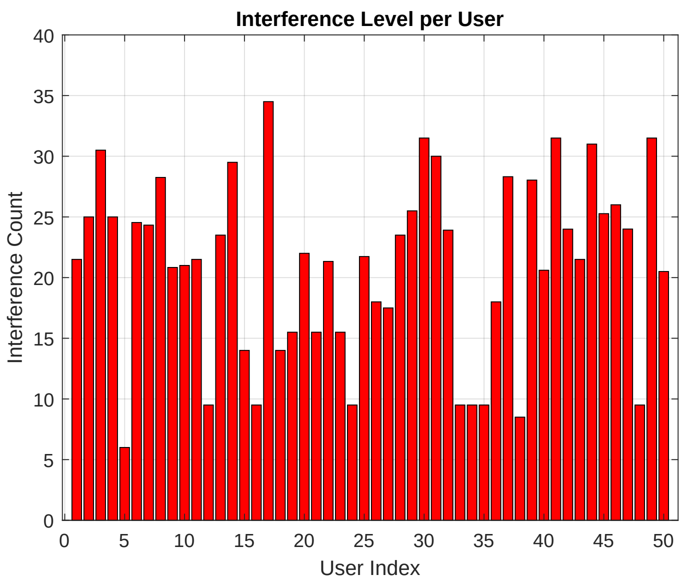

Figure 10: Interference level experienced by each user.

By combining K-means clustering (to structure the network into proximity-based groups) with conflict-graph coloring (to enforce interference-aware subchannel separation inside the reuse scenario), I provided a practical and scalable method to obtain reuse channel assignments that mitigate D2D→BS, CU→D2D, and D2D→D2D interference. This two-stage solution offers near-optimal behavior for large networks where solving the integer assignment formulation in the main optimization problem directly is computationally challenging, while still producing feasible channel reuse patterns suitable for subsequent power optimization.

Thesis 3.2 [J3]

I have developed a mobility-aware system modeling framework for D2D-underlay cellular networks using zone-based cell partitioning and Markov-based mobility prediction. The proposed model enables proactive estimation of channel gains and interference, providing an optimization-ready foundation for mobility-aware resource allocation. In this subthesis, I developed a mobility-aware system modeling framework that converts user movement in D2D-underlay cellular networks into a tractable and optimization-ready structure. I introduced a zone-based spatial division of the cell and designed a Markov transition model to predict user zone evolution over time, enabling proactive estimation of distance-dependent path loss variations and interference coupling before resource allocation is executed.

Zone-based spatial abstraction. I partitioned the cell of radius R_{cell} into N_{zones} concentric regions, which enables scalable location-aware modeling while avoiding continuous-coordinate complexity:

$$\Delta R = \frac{R_{\text{cell}}}{N_{\text{zones}}}, \qquad R_z = z\Delta R, \quad z \in \{1, \ldots, N_{\text{zones}}\}. \tag{33}$$

A user at radial distance r is mapped to a discrete zone state via:

$$R_{z-1} \leq r < R_z, \qquad R_0 = 0. \tag{34}$$

This mapping is later exploited to update channel gains and interference patterns using only zone transitions (instead of full tracking), yielding a practical trade-off between modeling granularity and runtime cost.

Mobility prediction via Markov state transitions. To capture macro-mobility, I modeled the user zone index $s(t) \in \{1, \ldots, N_{\text{zones}}\}$ as a Markov chain:

$$t_{z,z'} = \Pr\big(s(t+1) = z' \mid s(t) = z\big), \qquad \sum_{z'} t_{z,z'} = 1, \tag{35}$$

which enables probabilistic prediction of future zone distributions. This directly supports proactive interference estimation since path loss and cross-tier coupling depend on the zone-dependent distances.

Unified channel and SINR modeling under spectrum reuse. I derived a unified channel gain model combining large-scale path loss and small-scale Rayleigh fading:

$$g_{i,k}^{(j)}(t) = h_{i,k}^{(j)}(t) \cdot \frac{\beta}{d_{i,k}(t)^{\alpha}}, \qquad h_{i,k}^{(j)}(t) \sim \mathcal{CN}(0,1), \tag{36}$$

where $d_{i,k}(t)$ is time-varying due to mobility and α is the path loss exponent. Based on (36), I formulated explicit SINR expressions for both tiers under channel reuse:

(i) D2D receiver SINR:

$$\gamma_{i,k}^{(j)}(t) = \frac{P_i^{(j)}(t)\, g_{i,k}^{(j)}(t)}{\underbrace{\sum_{\substack{m\in\mathcal{U}_{\mathrm{D2D}}\\ m\neq i}} P_m^{(j)}(t)\, g_{m,k}^{(j)}(t)}_{I_{\mathrm{D2D}}^{(j)}(t)} + \underbrace{\sum_{n\in\mathcal{U}_{\mathrm{CU}}} P_n^{(j)}(t)\, g_{n,k}^{(j)}(t)}_{I_{\mathrm{CU}}^{(j)}(t)} + N_0}, \tag{37}$$

(ii) Cellular uplink SINR at the BS:

$$\gamma_{n}^{(j)}(t) = \frac{P_n^{(j)}(t)\, g_{n,\mathrm{BS}}^{(j)}(t)}{\underbrace{\sum_{i\in\mathcal{U}_{\mathrm{D2D}}} P_i^{(j)}(t)\, g_{i,\mathrm{BS}}^{(j)}(t)}_{I_{\mathrm{D2D}\to\mathrm{BS}}^{(j)}(t)} + N_0}. \tag{38}$$

Stability-oriented power feasibility region. To ensure the model is directly usable in later optimization stages (channel assignment and power control), I imposed bounded transmission powers for all users and channels:

$$0 \le P_x^{(j)}(t) \le P_{\max}, \qquad \forall x \in \mathcal{U}_{\mathrm{CU}} \cup \mathcal{U}_{\mathrm{D2D}},\ \forall j \in \mathcal{N}, \tag{39}$$

which prevents interference blow-up and preserves feasibility under mobility-driven distance changes.

By combining the discrete zone-state abstraction (34), Markov mobility prediction (35), and the interference-explicit SINR formulations (37)–(38) under bounded power (39), I created an optimization-ready modeling layer that enables proactive, mobility-aware updates of channel gains and interference. This modeling contribution serves as the core foundation for the resource allocation algorithms introduced in the subsequent subtheses (mobility-aware multi-objective optimization and stability-aware control integration).

Thesis 3.3 [J3]

I have formulated a joint resource allocation optimization problem for D2D-underlay cellular networks that maximizes total cellular and D2D throughput under spectrum reuse, QoS, and power constraints. The proposed formulation provides a unified optimization-ready foundation for mobility-aware channel assignment and power control. In this subthesis, I formulated a joint resource allocation optimization problem for D2D-underlay cellular networks that maximizes the aggregate throughput of both tiers while explicitly accounting for spectrum reuse, interference coupling, and mobility-driven SINR variations. The resulting formulation provides the optimization-ready foundation for the solution frameworks introduced later in this thesis group.

Joint throughput objective under spectrum reuse. I defined the total network throughput as the sum of the cellular and D2D throughput components:

$$\text{Maximize} \quad T_{\text{total}} = T_{\text{CU}} + T_{\text{D2D}}. \tag{40}$$

The cellular throughput is expressed as:

$$T_{\text{CU}} = \sum_{j \in \mathcal{N}} \sum_{n \in \mathcal{U}_{\text{CU}}} B_j \log_2 \left(1 + \gamma_n^{(j)}(t)\right), \tag{41}$$

while the D2D throughput explicitly incorporates the binary channel assignment decision variable $x_{i,j} \in \{0, 1\}$:

$$T_{\text{D2D}} = \sum_{j \in \mathcal{N}} \sum_{(i,k) \in \mathcal{U}_{\text{D2D}}} x_{i,j}\, B_j \log_2 \left(1 + \gamma_{i,k}^{(j)}(t)\right). \tag{42}$$

This formulation captures the fundamental coupling between *channel reuse decisions* ($x_{i,j}$) and *link quality* (via SINR), which is time-varying under mobility.

QoS constraints via minimum SINR guarantees. To ensure quality-of-service (QoS) for both tiers, I enforced minimum SINR thresholds:

$$\gamma_{i,k}^{(j)}(t) \geq \gamma_{\text{D2D,min}}, \quad \forall (i,k) \in \mathcal{U}_{\text{D2D}}, \quad j \in \mathcal{N}, \tag{43a}$$

$$\gamma_n^{(j)}(t) \geq \gamma_{\text{CU,min}}, \quad \forall n \in \mathcal{U}_{\text{CU}}, \quad j \in \mathcal{N}. \tag{43b}$$

These constraints are critical in interference-prone spectrum reuse settings and become more challenging under mobility due to time-varying interference and channel gains.

Power feasibility region. To regulate both energy usage and interference, I constrained the transmit powers of all users on all channels:

$$0 \leq P_x^{(j)}(t) \leq P_{\max}, \quad \forall x \in \mathcal{U}_{\text{D2D}} \cup \mathcal{U}_{\text{CU}}, \quad j \in \mathcal{N}. \tag{44}$$

Spectrum reuse and assignment constraints. To maintain implementable reuse behavior, I imposed allocation constraints on the binary assignment variables:

$$\sum_{j \in \mathcal{N}} x_{i,j} \leq 1, \quad \forall i \in \mathcal{U}_{\text{D2D}}, \tag{45a}$$

$$\sum_{i \in \mathcal{U}_{\text{D2D}}} x_{i,j} \leq N_{\text{reuse}}, \quad \forall j \in \mathcal{N}. \tag{45b}$$

These constraints ensure that each D2D pair uses at most one channel at a time and that each cellular channel is reused by at most N_{reuse} D2D pairs to prevent excessive interference.

Implementation trade-offs under mobility. I analyzed how enforcing QoS, power, and reuse constraints introduces practical trade-offs in mobile settings. In particular, the joint optimization is NP-hard due to the binary variables and SINR coupling, motivating heuristic or evolutionary approaches. Moreover, mobility increases the need for frequent reallocation (higher signaling overhead), while overly frequent updates may threaten stability; conversely, slower updates preserve stability but reduce responsiveness to mobility-induced congestion and interference fluctuations.

By formulating the joint throughput-maximization problem (40)–(42) under explicit QoS constraints (43a)–(43b), power feasibility (44), and spectrum reuse constraints (45a)–(45b), I established a unified, mobility-relevant optimization foundation for joint channel assignment and power control in D2D-enabled cellular networks. This formulation directly motivates the multi-objective and mobility-aware solution methods introduced in the subsequent subtheses.

Thesis 3.4 [J3]

I have developed a mobility-aware multi-objective resource allocation framework for D2D-underlay cellular networks based on NSGA-II. The proposed method jointly optimizes throughput, interference, and fairness, producing Pareto-efficient channel assignment and power control policies under mobility. In this subthesis, I developed a multi-objective optimization framework based on the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to solve the joint D2D-underlay resource allocation problem. The key novelty is treating *throughput maximization*, *interference mitigation*, and *fairness preservation* as concurrent objectives, and using NSGA-II to generate Pareto-efficient resource allocation policies under the original system constraints.

Multi-objective formulation (original journal equations). I formulated the resource allocation as a Multi-Objective Optimization Problem (MOOP) with three objectives as defined in the journal. The first objective in (46) maximizes the *total network throughput* by jointly accounting for the cellular sum rate T_{CU} and the D2D sum rate T_{D2D}. The second objective in (47) minimizes the *aggregate interference* observed in the system by combining both intra-/cross-tier interference contributions (I_{D2D} and I_{CU}), which directly influences the achieved SINR levels and QoS feasibility. The third objective in (48) enforces *fair resource distribution* using Jain's fairness index, where $J(\mathbf{c}) \in [0, 1]$ and larger values indicate more equal throughput allocation across all users $u \in \mathcal{U}$ (with $J(\mathbf{c}) = 1$ representing perfect fairness).

$$f_1(\mathbf{c}) = T_{\mathrm{total}} = T_{\mathrm{CU}} + T_{\mathrm{D2D}}, \tag{46}$$

$$f_2(\mathbf{c}) = I_{\mathrm{total}} = I_{\mathrm{D2D}} + I_{\mathrm{CU}}, \tag{47}$$

$$f_3(\mathbf{c}) = J(\mathbf{c}) = \frac{\left(\sum_{u\in\mathcal{U}} T_u\right)^2}{|\mathcal{U}| \sum_{u\in\mathcal{U}} T_u^2}, \quad 0 \le J \le 1. \tag{48}$$

Joint decision variables. NSGA-II optimizes the same two decision components: (i) the binary channel assignment $x_{i,j}$ (as used in the D2D throughput definition), and (ii) the continuous transmission power levels $P_x^{(j)}(t)$ (bounded by the power constraints).

Constraint-aware evolutionary search. To ensure feasible solutions, the optimization is carried out subject to the QoS, power, and reuse constraints defined in the main problem.

Algorithm 8 NSGA-II with Mobility Integration

Input: N_p, $G_{\max}$, P_m=0.01, P_c=0.8, η_c=20, η_m=20
Output: Pareto-optimal solutions $\mathcal{P}^*$
Phase 1: Initialize Population
Encode chromosomes: binary $x_{i,j} \in \{0,1\}$ and continuous $P_i^{(j)} \in [0, P_{\max}]$; initialize $\mathbf{p}_u$ (zone partitions)
for $g = 1$ to $G_{\max}$ **do**
  Phase 2: Update User Positions & Compute Channel Gains
  for each $u \in \mathcal{U}_{\text{CU}} \cup \mathcal{U}_{\text{D2D}}$ **do**
    Update macro-mobility using Markov chain $\mathbf{T}$
    Apply intra-zone motion:
    $x_i(t+\Delta t) = x_i(t) + v_i \cos\theta_i \Delta t + \mathcal{N}(0, \sigma_z^2)$
    $y_i(t+\Delta t) = y_i(t) + v_i \sin\theta_i \Delta t + \mathcal{N}(0, \sigma_z^2)$
  end for
  $G_{i,k}^{(j)}(t) = \dfrac{\beta}{d_{i,k}(t)^{\alpha}} h_{i,k}^{(j)}(t) \left(1 + \mathcal{N}(0, \sigma_{\text{CSI}}^2)\right)$
  Phase 3: Repair SINR Violations
  for each $u \in \mathcal{U}$ **do**
    while $\gamma_u < \gamma_{\min}$ **and** $P_u < P_{\max}$ **do**
      $P_u \leftarrow P_u + 0.1 P_{\max}$; update γ_u
    end while
    if $\gamma_u < \gamma_{\min}$ **then**
      Deactivate user: $x_{u,j} = 0,\ \forall j$
    end if
  end for
  Phase 4: Evaluate Fitness
  Throughput: $T_{\text{total}} = \sum_j \sum_u R_u^{(j)}$
  Interference: $I_{\text{total}} = \sum_j \left(I_{\text{D2D}}^{(j)} + I_{\text{CU}}^{(j)}\right)$
  Fairness: $J(\mathbf{c}) = \dfrac{(\sum T_u)^2}{|\mathcal{U}| \sum T_u^2}$
  if any $\gamma_u < \gamma_{\min}$ **then**
    Penalize fitness values
  end if
  Phase 5: Evolutionary Operators
  Apply SBX crossover, polynomial mutation, non-dominated sorting, and crowding distance
  Phase 6: Constraint Enforcement & Population Update
  for each D2D pair i **do**
    if violates constraints **then**
      Deactivate random channels
    end if
  end for
  Merge parents and offspring, then select top N_p individuals
end for

This contribution provides a practical multi-objective optimization engine that produces Pareto-optimal trade-offs between throughput, interference, and fairness under the original QoS, power, and spectrum reuse constraints, enabling resource allocation policies suitable for D2D-enabled cellular networks.

Simulation-based validation under mobility. To validate the effectiveness of the proposed mobility-aware NSGA-II in dynamic environments, I evaluated its performance against baseline approaches (static NSGA-II and greedy allocation) as user mobility speed increases. The results are organized around three key outcomes: throughput preservation, interference mitigation, and fairness robustness.

1) Throughput robustness versus mobility. Figure 11 reports the total system throughput as a function of user mobility speed. The results show that the proposed mobility-aware NSGA-II achieves consistently higher throughput than the baseline methods. Importantly, it maintains stable throughput across different mobility levels, whereas static NSGA-II and greedy allocation experience noticeable throughput degradation due to limited adaptability to mobility-driven SINR and interference variations.

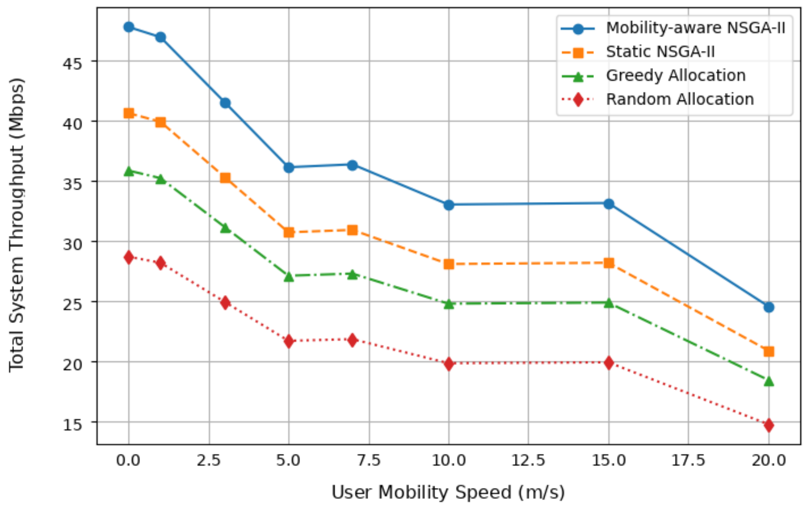

Figure 11: Total system throughput vs. user mobility speed.

2) Interference control under mobility. Figure 12 presents the average interference power versus user mobility speed. As mobility increases, both cross-tier and intra-tier interference tendencies become more pronounced. The proposed mobility-aware NSGA-II mitigates these interference fluctuations by dynamically adjusting channel assignment and power levels, yielding lower interference compared to static NSGA-II and greedy allocation.

3) Fairness preservation with increasing mobility. Figure 13 illustrates the impact of mobility on fairness using Jain's Index. While fairness decreases for all approaches as user velocity increases (due to frequent mobility-induced spectral conflicts and allocation instability), the mobility-aware NSGA-II maintains higher fairness levels than static and

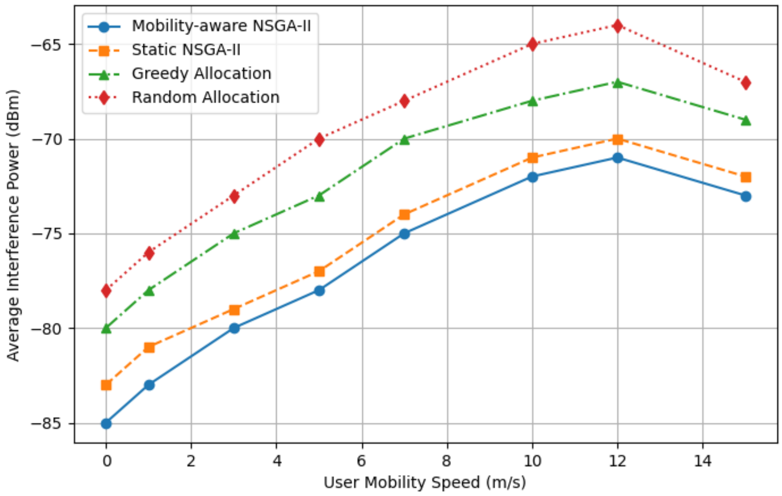

Figure 12: Average interference power vs. user mobility speed.

greedy methods. This confirms that the proposed multi-objective design better balances performance across users under dynamic movement.

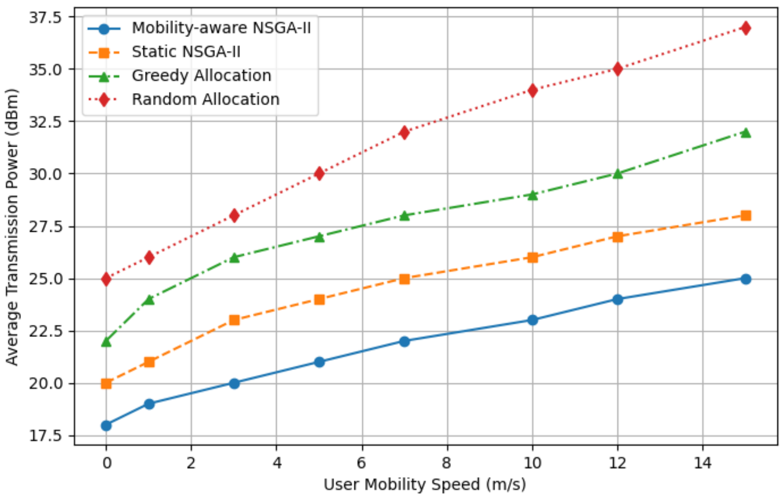

Figure 13: Impact of user mobility on power allocation.

Thesis 3.5 [J3]

I have integrated Lyapunov drift-plus-penalty optimization into the mobility-aware NSGA-II framework to enable stability-aware resource allocation under dynamic user mobility. The proposed approach combines virtual-queue tracking with multi-objective optimization to balance long-term QoS stability, throughput, and interference control. In this subthesis, I integrated Lyapunov optimization theory into the proposed mobility-aware NSGA-II resource allocation framework to provide stability-oriented control under dynamic user mobility. The contribution introduces virtual-queue-based stability tracking and a drift-plus-penalty objective that explicitly balances long-term QoS stability with short-term performance (throughput maximization and interference control), while preserving the multi-objective nature of the evolutionary optimizer.

System state and stability tracking I defined the system state at time t as:

$$\mathbf{x}(t) = \Big[\{\gamma_i(t)\}_{i=1}^{N_{\mathrm{CU}}+N_{\mathrm{D2D}}}, \{Q_u(t)\}_{u=1}^{N_{\mathrm{CU}}+N_{\mathrm{D2D}}}\Big],$$

where $\gamma_i(t)$ is the SINR of user i, and $Q_u(t)$ is a virtual queue tracking throughput deficit:

$$Q_u(t) = Q_u(t-1) + T_u^{\mathrm{target}} - T_u(t).$$

Lyapunov function and drift formulation (original journal equations). To quantify both SINR deviations and throughput imbalance, I adopted the Lyapunov function:

$$L(t) = \frac{1}{2} \sum_{i=1}^{N_{\mathrm{CU}}+N_{\mathrm{D2D}}} \left(\gamma_i(t) - \gamma_i^{\mathrm{target}}\right)^2 + \frac{1}{2} \sum_{u=1}^{N_{\mathrm{CU}}+N_{\mathrm{D2D}}} Q_u(t)^2, \tag{49}$$

and defined the conditional Lyapunov drift as:

$$\Delta(t) = \mathbb{E}[L(t+1) - L(t) \mid \mathbf{x}(t)]\,. \tag{50}$$

Using the journal derivation, the drift is upper bounded by:

$$\begin{aligned}\Delta(t) \le \mathbb{E}\Bigg[&\sum_{i=1}^{N_{\mathrm{CU}}+N_{\mathrm{D2D}}} \left(\gamma_i(t) - \gamma_i^{\mathrm{target}}\right)\left(\gamma_i(t+1) - \gamma_i(t)\right) \\ &+ \sum_{u=1}^{N_{\mathrm{CU}}+N_{\mathrm{D2D}}} Q_u(t)\left(T_u^{\mathrm{target}} - T_u(t)\right) \Big| \mathbf{x}(t)\Bigg] + B,\end{aligned} \tag{51}$$

where $B > 0$ captures bounded quadratic terms under bounded state transitions.

Drift-plus-penalty control objective (original journal equation). To enforce stability while optimizing performance, I formulated the drift-plus-penalty objective:

$$\text{Minimize: } \Delta(t) - V \cdot T_{\mathrm{total}}(t) + V \cdot I_{\mathrm{total}}(t), \tag{52}$$

where $V > 0$ controls the trade-off between long-term stability and short-term throughput/interference performance.

Formal stability guarantee (original journal theorem). The resulting stability guarantee is stated in the journal as:

Theorem 1 (Stability Guarantee). Under NSGA-II guided by the drift-plus-penalty framework:

1. All virtual queues remain bounded:

$$\limsup_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}[Q_u(\tau)] \le \frac{B + V(I_{\max} + T_{\max})}{\epsilon}$$

2. Time-average SINR deviations satisfy:

$$\limsup_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}\left[(\gamma_i(\tau) - \gamma_i^{\text{target}})^2\right] \leq \frac{2(B + V I_{\max})}{\epsilon}$$

where $I_{\max}$ and $T_{\max}$ are known bounds on interference and throughput, respectively, and $\epsilon > 0$ is a tunable convergence factor. ▪

Integration with NSGA-II (original journal description). I adapted NSGA-II to incorporate stability-oriented objectives by encoding control variables directly in the chromosome (power levels and channel assignments) and evaluating candidate solutions using stability and performance measures:

- **Chromosome Encoding:** Each solution includes power levels $P_i^{(j)}$ and channel assignments $x_{i,j}$.
- **Fitness Objectives:**

$$\begin{aligned} f_1 &= -\Delta(t) \quad \text{(Stability)} \\ f_2 &= T_{\text{total}}(t) \quad \text{(Throughput)} \\ f_3 &= -I_{\text{total}}(t) \quad \text{(Interference).} \end{aligned} \tag{53}$$

- **Constraint Handling:** Infeasible solutions are penalized or projected to the feasible region .

This contribution extends the mobility-aware NSGA-II resource allocation framework with stability-aware control guarantees by combining virtual-queue tracking, Lyapunov drift analysis, and drift-plus-penalty optimization. As a result, the resource allocation strategy is not only Pareto-efficient in throughput–interference trade-offs, but also formally guided toward bounded long-term behavior under mobility-driven variations.

8 Future Work

This dissertation advances resource allocation through optimization, clustering, and learning-based techniques; however, several extensions can further strengthen its applicability. The CUSF and FTPC frameworks could be extended to alternative multi-user schemes such as MU–LP and RSMA, while integrating user mobility and imperfect CSI to enhance robustness under realistic conditions. The MEC energy optimization model can evolve into a unified uplink–downlink framework incorporating stochastic user arrivals and dynamic workloads, with reinforcement learning or AI-based controllers enabling adaptive decision-making in real time. The D2D channel reuse schemes based on clustering and graph coloring may benefit from evolutionary and reinforcement learning–based graph embeddings to improve scalability and responsiveness, especially in heterogeneous networks with variable QoS demands. The mobility-aware NSGA-II optimization can be expanded using deep reinforcement learning and federated learning to enable distributed intelligence and privacy-preserving adaptation at the network edge. Finally, large-scale validation in 5G/6G testbeds and cross-layer integration with emerging technologies such as network slicing, URLLC, and AI-native RAN will be crucial to evaluate performance trade-offs and operational feasibility. Overall, refining learning-driven optimization, extending adaptability to diverse environments, and validating in live or emulated networks will guide the next phase of intelligent and energy-efficient resource management research.

9 Conclusion

This Ph.D. research presented a comprehensive framework for intelligent and energy-efficient resource allocation in 5G and beyond wireless networks. The study addressed major challenges in power control, channel assignment, interference management, and mobility-aware optimization, combining mathematical rigor with practical design insights. Each contribution built upon the previous one, resulting in a unified set of solutions that enhance both the efficiency and adaptability of modern communication systems.

In Thesis Group 1, I developed a hybrid optimization framework for NOMA–OFDMA systems. The proposed Channel User Sorting and Filling (CUSF) algorithm, integrated with the Fractional Transmit Power Control (FTPC) scheme, efficiently solved the non-convex and NP-hard joint channel and power allocation problem. This decomposition approach improved spectral efficiency while reducing computational complexity, forming a strong foundation for optimized multi-user access in NOMA networks.

In Thesis Group 2, I focused on energy-efficient computation offloading in Mobile Edge Computing (MEC) environments. A comprehensive optimization framework was introduced to minimize total energy consumption across both local and remote processing tasks. The study incorporated NOMA and massive MIMO (mMIMO) access schemes and employed convex optimization techniques to achieve optimal uplink power control under dynamic network conditions. The results highlighted the effectiveness of the proposed method in reducing energy use and balancing the trade-offs among delay, throughput, and overall performance.

Thesis Group 3 extended these ideas to Device-to-Device (D2D) communications, emphasizing interference management and mobility-aware optimization. I formulated the channel reuse problem as an Integer Linear Programming (ILP) model and proposed a scalable heuristic combining K-means clustering and graph coloring for efficient channel assignment. This was followed by a fairness-aware geometric programming method for power control, which ensured balanced SINR and equitable spectrum reuse. Additionally, I developed a mobility-aware multi-objective optimization framework based on the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), integrating Markov mobility prediction and Lyapunov drift analysis to guarantee system stability. The proposed algorithms demonstrated improved throughput, effective interference suppression, and enhanced fairness compared to static and greedy allocation schemes, confirming their robustness and adaptability under realistic mobility conditions.

Collectively, the contributions of this dissertation establish a unified and forward-looking strategy for intelligent resource allocation in next-generation wireless networks. The integration of optimization theory, mobility modeling, and learning-inspired algorithms provides a strong foundation for energy-efficient and scalable 6G systems. The research outcomes confirm that combining mathematical modeling with adaptive decision-making can significantly enhance efficiency, fairness, and network performance, positioning this work as a meaningful step toward self-optimizing and mobility-resilient communication infrastructures.

List of Publications

Journals

J1. **Qusay Alghazali**, Husam Al-Amaireh, Tibor Cinkler, "Joint Power and Channel Allocation for Non-Orthogonal Multiple Access in 5G Networks and Beyond", *Sensors*, Vol. 23, No. 19, 2023, Article 8040. DOI: 10.3390/s23198040. (WoS, Impact Factor: 3.4, Scopus, CiteScore: 7.3, **Q1**).

J2. **Qusay Alghazali**, Husam Al-Amaireh, Tibor Cinkler, "Energy-Efficient Resource Allocation in Mobile Edge Computing Using NOMA and Massive MIMO", *IEEE Access*, Vol. 13, 2025, pp. 21456–21470. DOI: 10.1109/ACCESS.2025.3535233. (WoS, Impact Factor: 3.4, Scopus, CiteScore: 9.8, **Q1**).

J3. **Qusay Alghazali**, Husam Al-Amaireh, Tibor Cinkler, "Mobility-Aware Resource Allocation in D2D Communications Using Genetic Algorithms," *IEEE Access*, Vol. 13, 2025, pp. 144591–144606. DOI: 10.1109/ACCESS.2025.3599051. (WoS, Impact Factor: 3.4; Scopus, CiteScore: 9.8, **Q1**).

Additional Journals in Progress

A1. *Qusay Alghazali, Abdulbasit M. A. Sabaawi, Husam Al-Amaireh, Mohammed R. Almasaoodi, and Tibor Cinkler, "Quantum Genetic Algorithm-Based Joint User Grouping and Power Control for Energy Efficiency Optimization in Multi-Cell Massive MIMO Uplink Systems," To be submitted to Springer Journal of Quantum Information Processing.*

A2. *Qusay Alghazali, Husam Al-Amaireh, and Tibor Cinkler, "Beamforming-Aware Joint Resource and Power Allocation for Energy-Efficient Task Offloading in Massive MIMO MEC Networks," To be submitted to Springer.*

2. Conferences

C1. **Qusay Alghazali**, Husam Al-Amaireh, Tibor Cinkler, "Graph Coloring and User Clustering-Based Resource Allocation for Device-to-Device Communication in 5G Networks", *2025 5th International Conference on Electrical, Computer and Energy Technologies (ICECET)*, Paris, France, 3–6 July 2025. IEE XPlore https://doi.org/10.1109/ICECET63943.2025.11472411

C2. Viktória Nemkin, **Qusay Alghazali**, Tibor Cinkler, Katalin Friedl, László Kabódi, "Experiments with QUBO on D-Wave", Technical Report, Budapest University of Technology and Economics (BME), 2023. Available at: https://www.bme.hu

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