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Enhancing Network Metrics by Utilizing MIMO and mmWave for ORAN Dynamic Multi-Objective Optimization

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ABSTRACT

In this manuscript, we present a complete multiobjective optimization methodology which aims at handling these challenges by the incorporation of MIMO as well as mmWave techniques. The optimization model considers energy efficiency (EE), spectral efficiency (SE), and user (UE) fairness as the three most important performance indicators while complying with practical constraints, such as power and bandwidth limitations, interference control policies and dynamic channel conditions. The optimization is solved through advanced techniques as the sequential quadratic programming (SQP), active set, and interior point to solve the power allocation, beamforming strategies, and resource distribution for UEs. In addition, this work proposed an interference-aware power and bandwidth allocation scheme while meeting the QoS constraints. We take into account the time-varying characteristics of wireless channels and design of dynamic power allocation strategies that reflect UE mobility and variations in channel conditions. We also added energy harvesting functions to make the network more sustainable and less reliant on traditional power supplies. The simulation is applied to three case studies to achieve high EE, SE, and fairness in various real network scenarios. The results demonstrate that SQP outperforms active set and interior point methods, especially in the presence of high interference and dynamics by offering more reliable and light-weight nature resource allocation. In addition, the introduction of mmWave to MIMO substantially enhances the system capacity and low latency especially in cases where there is a demand for high data rate transmission.

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1. INTRODUCTION

The need for ultra-high data rates, low latency, and strong reliability in wireless communications has been increasing significantly with the emerging proliferation of mobile networks, IoT, autonomous driving, as well as augmented and virtual reality [1] [2]. Hence, the open radio access network (ORAN) system has emerged as a solution to fulfill these requirements. ORAN follows a three-tier architecture of centralized unit, distributed unit (DU) and radio unit (RU). The CU is responsible of upper layers such as radio resources management, mobility management, packet data convergence protocol, and RAN control. The DU processes real-time functions such as

MAC, radio link control and physical layer, it is closer to the user for low latency. The RU is responsible for wire-level transmission and reception of radio waveforms over the air-interface including beam forming and signal processing. Those functions are virtualized and defined by the ORAN Alliance's functional split that can brought to life by more than one vendors. However, future wireless systems are heavily exploiting two fundamental techniques, MIMO and mmWave communication. As wireless technology has entered the multiple-input and multiple-output (MIMO) era, which can provide high data rate by spatial multiplexing and beamforming, MIMO systems have become an essential infrastructure of wireless communication. On the other hand, mmWave communication is promising to provide a large bandwidth due to limited number of devices and can be used at high frequencies leading to increase in the capacity, such that data transmission for short range applications could be feasible. Hence, in an ORAN system, the integration of MIMO and mmWave technologies becomes crucial and interested to be investigated. ORAN's architecture allows for the virtualization of network functions and software-defined networking, enabling efficient management and real-time optimization of resources. As ORAN facilitates dynamic resource allocation across virtualized network functions, it can leverage the massive bandwidth and beamforming capabilities of mmWave and the spatial diversity and multiplexing of MIMO to optimize system capacity and coverage. This adaptability is essential in a rapidly changing environment, where network load and user demands fluctuate continuously [3]. Although employing these technologies provides various benefits, introducing and tuning optimal operation of these techniques in realistic systems is faced with several challenges, ranging from resource allocation to interference management and QoS provisioning under dynamic environments. low-level MIMO and mmWave need to be carefully designed and coordinated for optimal performance. The allocation of power and bandwidth, the appropriate choice of beamforming strategy, as well as UE fairness are introduced to be optimized for resource efficient usage, capacity improvement and service fair between UEs. However, the integration of MIMO and mmWave technologies within an ORAN system requires a highly adaptive and flexible network. The nature of mmWave signals, which are prone to high path loss and limited range, necessitates dense network deployments and advanced techniques like beamforming and adaptive power control. Similarly, MIMO systems require effective interference management and resource allocation, which can be challenging in highly dynamic and congested environments. The open and virtualized architecture of ORAN allows these challenges to be addressed efficiently by enabling real-time optimization, intelligent network management, and dynamic resource allocation, all crucial for mmWave and MIMO systems to perform optimally. In addition, with the growing complexity of today's systems, it is necessary to formulate advanced optimization models that can handle many conflicting objectives at a time. Such criteria may include energy-spectral-fair-efficient system with robust performance under different channel conditions concurrent with interference caused by other UEs and variations in the network loads. However, there is an inherent trade-off between satisfying these objectives in next generation wireless networks. In modern wireless systems, a critical issue is how to allocate resources (e.g. powers, bandwidths and the beamforming vectors) in an effective way to maximize the system performance. A promising solution to these problems is the consolidation of mmWave and MIMO technology. For instance, mmWave technology can help resolve the bandwidth delay encountered in typical wireless communication systems where wide band high frequency bands are introduced with relatively less congestion to enable higher data rate and capacity [4]. This is quite crucial for facilitating new applications such as smart cities that are in need of an extremely large data rate with negligible delay. [5] stresses the significance of resource management in mmWave MIMO systems, and argue that optimal power and bandwidth allocation is required for achieving high system utility while providing QoS provisioning to UEs. They provide a review of how effective allocation of resources can handle interference, deal with UE fairness, and dealing with the balancing between energy and spectral efficiency. These techniques are the key to obtaining the desired performance either in dense urban areas or if scaling up to large wireless networks.In addition, the application of MIMO and mmWave technologies also helps combat the limitations of ultra-reliable low latency communication, which is essential for use cases like autonomous driving and industrial automation. This combination of MIMO and mmWave can improve system reliability and minimize latency, representing two key research challenges in modern communication networks. These technologies achieve greater spectrum utilization efficiency due to the optimization of beamforming and channel estimation techniques thereby achieving higher data rates with reduced interference [6]. Additionally, the authors of [7] provide a detailed review of mmWave communication challenges and solution advancements with a focus on dealing with the time-varying nature of the mmWave channel, such as loS/NLoS communications, for instance, through advanced channel modeling and also beamforming. These are important breakthroughs to achieve the operational efficiency of mmWave communications, especially under high mobility and time-varying traffics. Opportunities also abound in the fusion of energy harvesting with MIMO and mmWave systems to better enhance the greenness of wireless networking. In [8], it was explored how energy harvesting can be used to augment power consumption, shifting the reliance from the conventional power grid and making the networks greener. This is of particular interest for next generation networks targeting a trade-off between performance and EE. Also in [9], opportunities and challenges of integrating MIMO with mmWave systems for 5G networks are presented, the need for dynamic spectrum sharing and efficient resource management are highlighted. The combination of these technologies offers a route to higher SE and UE fairness, two key features that will make the performance of next-generation wireless systems. This combination not only improves the system capacity, it also serves to reduce interference and maximize signal rates, thereby enhancing the end UE experience. Although much work has been carried out in the studies of MIMO and mmWave systems and their potentials for future communications, several main gaps exist in current literature. Existing researches tend to be largely theoretical on such technologies and lack focus on their integration and real-life challenges. Remarkably, there are no yet “full-spectrum” multi-objective optimization frameworks successfully integrating and unifying the benefits of MIMO and mmWave networks to adapt with dynamic and unpredictable characteristics presented in 5G wireless environments. Also, although EE and fairness are regarded as important QoE metrics, several models lack to balance QoE with spectrum efficiency under the strict demands of 5G communication systems. The combination of energy harvesting, which is an emerging key part in green communications, with massive MIMO and mmWave has not been well considered. Another unexplored aspect is the real-time interference that causes the network to be dynamically affects the mobility or energy availability. Furthermore, most of the prior work concerning mmWave MIMO systems ignores some practical constraints including SINR thresholds, data rate requirements and channel quality conditions. In many optimization models, these constraints are either caricatured or abstracted with little attention is paid to them while in practice, such predictions give way to several challenges during deployment of a large scale systems. This work further considers several major performance metrics (e.g., EE, SE, UE fairness and interference management) simultaneously. Most previous approaches optimize only one or two of these goals while ignoring the trade-offs that may be caused when optimizing multiple objectives together. Finally, fair UEs and how to maintain fairness in the sense that all UEs get a fair share of resources needs more attention. Most models disregard fair allocation, or not in a complete direction, and more importantly do not balance it well with other objectives such as energy consumption and SE. This gap is exactly important as the understanding about how to achieve fair allocation in multi-UE systems while not degrading other performance metrics. Therefore, it is apparent that a significant research gap exists for those models which take into account an overall allocation approach of the resources in MIMO and mmWave systems under realistic assumptions. In an effort to fill these gaps, in this paper we develop a generic and scalable multi-objective optimization framework which incorporates these ingredients in a unified model that includes three coherent phases. These aimed to enhance the performance and EE of next-generation wireless systems by integrating MIMO, mmWave systems, as well real-world constraints like dynamic channels, energy harvesting and UE fairness.

2. RELATED WORKS

Recent advancements in MIMO and mmWave technologies have led to various optimization models aimed at enhancing the performance of wireless communication systems. However, many of these models exhibit limitations when compared to the integrated approach proposed in this paper. Below is a review of 15 pertinent studies, highlighting their contributions and identifying areas where they fall short relative to the proposed model. The authors of [10] analyzed the trade-off between EE and SE in MIMO-NOMA systems, aiming to maximize both while ensuring equal data rates for all UEs. However, it does not consider UE fairness or dynamic channel conditions, which are critical in real-world scenarios. In addition, the work in [11] proposes methods for UE grouping and dynamic power allocation in MIMO-NOMA systems. While it addresses energy harvesting, it overlooks the integration of spectral efficiency and UE fairness, which are vital for balanced system performance. Whereas [12] presents an algorithm to balance SE and EE in massive MIMO systems. However, this work does not incorporate UE fairness or interference management, which are essential for equitable resource distribution. The study [13] provides an efficient precoding technique for mmWave massive MIMO with deep learning. However, it does not incorporate energy harvesting or UE fairness, which are essential for sustainable and equitable system performance. The work in [14] investigated one EE problem for Massive MIMO with imperfect CSI, i.e., minimize the power consumption of a network subject to SE constraints. To make the problem tractable, it adopts a difference-of-convex programming algorithm which aims at finding sub-optimal solutions in an efficient manner, significantly outperforming traditional schemes such as MRT and ZFP especially at low SNR. However, the contribution misses several aspects such as multi objective optimization, interference scenarios are not taken into account, mmWave provisioning analysis and dynamic channel

during time-varying scenario and energy harvesting. The work of [15] considers the EE maximization problem for mmWave MIMO-NOMA systems. It also introduces a user clustering and power allocation algorithm aiming at the tradeoff between EE and system capacity in dense network scenarios. However, the paper suffers from certain drawbacks like absence of multi-objective optimization, alternate interference management, static channel scenario and energy harvesting schemes. In [16], the paper investigates beamforming and power allocation in IRS-assisted mmWave systems. While it addresses beamforming, it does not consider energy harvesting or UE fairness, which are crucial for comprehensive system optimization. Furthermore, [17] proposes a hybrid design for mmWave MIMO systems, maximizing spectral efficiency. It does not address EE, fairness, or interference management, which are essential for balanced system performance. Whereas [18] presentd a resource allocation scheme for MIMO-NOMA networks with energy harvesting capabilities. However, it does not fully incorporate mmWave characteristics, which would enhance the understanding of resource allocation in high-frequency systems. Followed by [19] that focused on beamforming strategies to optimize spectral and EE, it does not incorporate real-time interference management, a crucial aspect for ensuring stable performance in densely populated environments. Finally, [20] explored power control and beamforming optimization in mmWave MIMO systems with energy harvesting. Although it considers EE, it lacks a focus on fairness between UEs and the dynamic adaptation to varying network conditions.
The analyzed articles provide interesting trends on various aspects of MIMO and mmWave systems.

3. SYSTEM MODEL

3.1. MIMO channel model

In a MIMO system with (N_r) receive antennas and (N_t) transmit antennas, the channel matrix ($H \in C^{N_r \times N_t}$) describes the propagation of signals between the base station and UE. The received signal at UE (i) that is served by RU r and distributed unit d is:

$$y_{i,r,d} = H_{i,r,d} x_{i,r,d} + n_{i,r,d}$$

Where $H_{i,r,d}$ is the channel matrix for UE (i), RU r and distributed unit d, ($x_{i,r,d}$) is the transmitted signal vector, and $n_{i,r,d}$ is the noise vector at UE (i). The capacity of the MIMO link for UE (i) is given by the Shannon Capacity formula:

$$C_{i,r,d} = \log_2\left(\det\left(I_{N_r} + \frac{P_{i,r,d}}{N_0} H_{i,r,d} H_{i,r,d}^H\right)\right)$$

Where $P_{i,r,d}$ is the power allocated to UE (i), RU r and distributed unit d, (b{I}_{N_r}) is the identity matrix of size (N_r), and N_0 is the noise power spectral density.

3.3 Beamforming Model

Beamforming is employed to direct the signal energy towards specific UEs and minimize interference. The beamforming vector for UE (i), RU r and distributed unit d, using Zero-Forcing (ZF) beamforming, is:

$$w_{i,r,d} = \left(H_{i,r,d} H_{ir,d}^H\right)^{-1} H_{i,r,d}^H$$

This maximizes the SINR (Signal to Interference plus Noise Ratio) for UE (i), RU r and distributed unit d, ensuring optimal power allocation.

3.4 Interference Model in MIMO

In the presence of multiple UEs, interference is inevitable. The total interference ($I_{i,r,d}$) for UE (i), RU r and distributed unit d from other UEs is modeled as:

$$I_{i,r,d} = \sum_{j \neq i} P_j \left| H_{i,r,dw_j} \right|^2$$

Thus, the total SINR for UE (i) is:

$$SINR_{i,r,d} = \frac{P_{i,r,d} \left| H_{i,r,d} w_{i,r,d} \right|^2}{N_0 + I_{i,r,d}}$$

Where (P_j) is the power allocated to UE (j). The mmWave channel is characterized by multiple paths, typically involving line-of-sight (LoS) and non-line-of-sight (NLoS) paths. The channel (H_{mmWave}) for UE (i), RU r and distributed unit d is modeled as:

$$HmmWave = \sum l = 1^L \alpha_l a(\theta_{T,l}) a^H(\theta_{R,l})$$

Where L is the number of propagation paths, (α_l) is the complex gain of the l-th path, ($a(\theta_{T,l})$) and (ꟻb{a}($\theta_{R,l}$)) are the transmit and receive array response vectors. For mmWave, the path loss is more significant, and the path loss model depends on the distance (d), the carrier frequency (f), and the environment. The path loss ($L(d)$) can be written as:

$$L(d) = L_0 + 10\gamma \log_{10}(d) + 10\eta \log_{10}(f)$$

Where (L_0) is the reference path loss at (d_0), (γ) is the path loss exponent (typically between 2 and 6 for mmWave), (η) is the frequency dependence factor, and (f) is the operating frequency. However, the mmWave capacity with beamforming is given by:

$$C_{mmWave} = \log_2 \left(\det \left(IN_r + \frac{P_{i,r,d}}{N_0} HmmWaveH_{mmWave}^H \right) \right)$$

This is similar to the MiMo capacity formula but adjusted for the mmWave channel characteristics.

3.5 Optimization Objectives

We optimize the following multi-objective functions:

1. Energy efficiency: EE is the ratio of the total data rate to the total power consumption:

$$E_{eff} = \frac{\sum_{i,r,d} R_{i,r,d}}{\sum_{i,r,d} P_{i,r,d}}$$

Where ($R_{i,r,d}$) is the data rate of UE (i) from RU r and distributed unit d, and ($P_{i,r,d}$) is the power allocated to UE i from RU r and distributed unit d.

2. Spectral Efficiency (SE): Spectral efficiency is the total data rate divided by the total bandwidth:

$$SE = \sum_{i,r,d} B \log_2 \left(1 + \frac{P_{i,r,d} H_{,r,d}}{N_{i,r,d}} \right)$$

Where ($H_{i,r,d}$) is the channel gain and ($N_{i,r,d}$) is the noise power, RU r and distributed unit d.

3. UE Fairness (F): Fairness is modeled using Shannon entropy to ensure equitable distribution of resources:

$$F = -\sum_{i,r,d} \frac{P_{i,r,d}}{\sum_j P_j} \log_2 \left(\frac{P_{i,r,d}}{\sum_j P_j} \right)$$

The overall optimization problem is to maximize the weighted sum of EE, spectral efficiency, and fairness:

$$\text{Maximize } Z = \alpha_1 E_{eff} + \alpha_2 SE + \alpha_3 F$$

Subject to:

1. Power Constraint:

$$\sum_i P_{i,r,d} \leq P_{max}$$

2. Data Rate Constraint:

$$R_{i,r,d} \geq R_{min}$$

3. SINR Constraint:

$$SINR_{i,r,d} \geq SINR_{th}$$

4. Channel Quality Constraints:

$$CQ_{i,r,d} \geq CQ_{th}$$

1.1 Solving the system using Lagrange multiplier

$$Z = \alpha_1 E_{\text{eff}} + \alpha_2 SE + \alpha_3 F$$

We incorporate the constraints into the objective function using Lagrange multipliers. The Lagrangian ($\mathcal{L}$) is:

$$\mathcal{L} = \alpha_1 E_{\text{eff}} + \alpha_2 SE + \alpha_3 F + \lambda_1 \left(P_{\text{max}} - \sum_i P_{i,r,d} \right) +$$
$$\lambda_2 \left(\sum_{i,r,d} R_{i,r,d} - R_{\text{min}} \right) + \lambda_3 \left(SINR_{i,r,d} - \text{SINRth} \right) +$$
$$\lambda_4 (CQ_i - CQ_{\text{th}})$$

Where ($\lambda_1, \lambda_2, \lambda_3, \lambda_4$) are the Lagrange multipliers associated with the constraints. To maximize ($\mathcal{L}$), we take the partial derivatives of ($\mathcal{L}$)with respect to each decision variable and set them to zero.

1. Partial Derivative with respect to Power Allocation ($P_{i,r,d}$):

For EE (E_{eff}), we take the derivative:

$$\frac{\partial \mathcal{L}}{\partial P_{i,r,d}} = \frac{\partial}{\partial P_{i,r,d}} \left(\alpha_1 \frac{\sum_i R_{i,r,d}}{\sum_i P_{i,r,d}} \right) + \backslash$$
$$\frac{\partial}{\partial P_{i,r,d}} \left(\alpha_2 \sum_i \log_2 \left(1 + \frac{P_{i,r,d} H_{i,r,d}}{N_{i,r,d}} \right) \right) + \frac{\partial}{\partial P_{i,r,d}} (\alpha_3 F) - \lambda_1 = 0$$

For E_{eff}:

$$\frac{\partial}{\partial P_{i,r,d}} \left(\frac{\sum_i R_{i,r,d}}{\sum_i P_{i,r,d}} \right) = -\frac{R_{i,r,d}}{P_{i,r,d}^2}$$

The partial derivative of (SE) with respect to ($P_{i,r,d}$) is:

$$\frac{\partial}{\partial P_{i,r,d}}\left(\log_2\left(1+\frac{P_{i,r,d}H_{i,r,d}}{N_{i,r,d}}\right)\right)=\frac{H_{i,r,d}}{P_{i,r,d}H_{i,r,d}+N_{i,r,d}\ln(2)}$$

Fairness Derivative:

$$\frac{\partial}{\partial P_{i,r,d}}\left(-\frac{P_{i,r,d}}{\sum_j P_j}\log_2\left(\frac{P_{i,r,d}}{\sum_j P_j}\right)\right)=\frac{1}{P_{i,r,d}}-\frac{1}{\sum_j P_j}\ln(2)$$

2. Partial Derivative with respect to Data Rate ($R_{i,r,d}$):

For the data rate constraint ($R_{i,r,d} \geq R_{\min}$), we have:

$$\frac{\partial \mathcal{L}}{\partial R_{i,r,d}}=\alpha_1\frac{1}{\sum_i P_{i,r,d}}-\lambda_2=0$$

Thus, the equation becomes:

$$\alpha_1\frac{1}{\sum_i P_{i,r,d}}=\lambda_2$$

3. Partial Derivative with respect to SINR ($SINR_{i,r,d}$):

For SINR:

$$\frac{\partial \mathcal{L}}{\partial SINR_{i,r,d}}=-\lambda_3=0$$

Thus:

$$\lambda_3=0$$

4. Partial Derivative with respect to Channel Quality (CQ_i):

For channel quality (CQ_i):

$$\frac{\partial \mathcal{L}}{\partial CQ_i}=-\lambda_4=0$$

Thus:

$$\lambda_4=0$$

Solve the System of Equations

$$\frac{\partial \mathcal{L}}{\partial P_{i,r,d}}=0,\quad \frac{\partial \mathcal{L}}{\partial R_{i,r,d}}=0,\quad \frac{\partial \mathcal{L}}{\partial SINR_{i,r,d}}=0,\quad \frac{\partial \mathcal{L}}{\partial CQ_i}=0$$

The final equations to solve are:

$$\frac{\alpha_1}{P_{i,r,d}^2}+\frac{\alpha_2}{P_{i,r,d}H_{i,r,d}+N_{i,r,d}\ln(2)}+\frac{1}{P_{i,r,d}}-\frac{1}{\sum_j P_j}\ln(2)=\lambda_1$$

$$\alpha_1 \frac{1}{\sum_i P_{i,r,d}} = \lambda_2$$

4. SYSTEM MODEL WITH DYNAMIC ALLOCATION

The goal of this problem is to allocate resources (like power, spectral bandwidth, and beamforming vectors) to UEs in a multi-UE wireless network, ensuring that multiple performance objectives are met. These objectives include:

1- EE: maximizing the data rate per unit of power consumption.

2- SE: Maximizing the total data rate across all UEs, considering interference and noise.

3- UE Fairness: Ensuring that the resource allocation is fair among UEs, preventing the domination of a few UEs over others.

The problem becomes more complex due to factors like dynamic channel conditions, interference, and energy harvesting.

To solve this, we use a multi-objective optimization framework that maximizes a weighted sum of the above objectives subject to several constraints:

1. Power Constraints: The total power must not exceed a certain limit.
2. SINR Constraints: Each UE must maintain a minimum Signal-to-Interference-plus-Noise Ratio (SINR) to guarantee quality of service (QoS).
3. Data Rate Constraints}: Each UE must meet a minimum data rate.

We use Lagrange multipliers to incorporate these constraints into the objective function and find the optimal resource allocation.

4.1 Objective Function

The objective function is the weighted sum of EE, SE, and F. This is the function that we aim to maximize.

$$Z = \alpha_1 \frac{\sum_i R_{i,r,d}}{\sum_i P_{i,r,d}} + \alpha_2 \sum_i \log_2\left(1 + \frac{P_{i,r,d} H_{i,r,d}}{N_{i,r,d} + I_{i,r,d}}\right) +$$
$$\alpha_3 \left[-\sum_i \frac{P_{i,r,d}}{\sum_j P_j} \log_2\left(\frac{P_{i,r,d}}{\sum_j P_j}\right)\right] + \alpha_4 \sum_i SINR_{i,r,d}$$

4.2 Energy Efficiency

This term represents the ratio of total data rate to total power consumption. Maximizing this term ensures that the network delivers the maximum data rate for each unit of energy consumed. The goal is to design an energy-efficient system. If power allocation isn't optimized for EE, the system would consume unnecessary energy while delivering suboptimal throughput, as follows:

$$\frac{\sum_i R_{i,r,d}}{\sum_i P_{i,r,d}}$$

Spectral Efficiency:

$$\sum_i \log_2\left(1 + \frac{P_{i,r,d} H_{i,r,d}}{N_{i,r,d} + I_{i,r,d}}\right)$$

This term represents the SE, which is the total data rate across all UEs, taking into account interference from other UEs ($I_{i,r,d}$) and noise ($N_{i,r,d}$). Maximizing spectral efficiency ensures that the network uses the available spectrum in the most efficient way possible, improving the overall throughput.

UE Fairness (F): $\sum_i \frac{P_{i,r,d}}{\sum_j P_j} \log_2\left(\frac{P_{i,r,d}}{\sum_j P_j}\right)$

This term is based on Shannon entropy and is used to model UE fairness}. The fairness function ensures that power resources are distributed as equally as possible among UEs. UEs with less power receive higher fairness.Without fairness, some UEs might consume most of the available resources, leading to an imbalanced performance across the network. Fairness ensures that each UE gets a reasonable share of resources.

4.3 Power Allocation (Non-linear Model)

This equation models the non-linear power allocation for UE (i), RU r and distributed unit d, based on the distance ($d_{i,r,d}$) between the base station and the UE. The path loss exponent (γ) captures the loss in signal strength due to distance. The second factor reflects the fading effects and the channel quality of the UE. This non-linear model allows for a more realistic power allocation, where UEs farther from the base station or experiencing poor channel conditions are allocated more power.

$$P_{i,r,d} = \left(\frac{d_{i,r,d}}{d_0}\right)^{\gamma} \cdot \left(\frac{1}{1 + \alpha\left|h_{i,r,d}\right|^2}\right)$$

Where, ($\left|h_{i,r,d}\right|^2$) is the channel gain for UE (i), RU r and distributed unit d.

4.4 Beamforming Optimization (Zero-Forcing Beamforming)

This equation represents Zero-Forcing Beamforming (ZFBF), which is a method for optimizing the beamforming vector \($w_{i,r,d}$ \) to cancel interference from other UEs. The matrix ($H_{i,r,d}$) represents the channel between the base station and UE (i). Beamforming optimization helps direct the signal energy towards the intended UE and reduce interference from other UEs. ZFBF is a popular technique used in MIMO systems to handle interference.

$$w_{i,r,d} = \left(H_{i,r,d} H_{i,r,d}^H\right)^{-1} H_{i,r,d}^H$$

4.5 Interference Management

This equation models the interference ($I_{i,r,d}$) for UE (i) , RU r and distributed unit d, caused by other UEs. The interference depends on the power allocated to other UEs (P_j) and the beamforming vectors (w_j). The denominator models the interference attenuation. Managing interference is crucial in multi-UE wireless networks. Without interference management, the system would become inefficient and the SINR would drop drastically.

$$I_{i,r,d} = \sum_{j \neq i} \left(\frac{P_j \left|H_{i,r,dw_j}\right|^2}{1 + \alpha \left|H_{i,r,dw_j}\right|^2}\right)$$

4.6 Dynamic Channel Model

This equation models the time-varying channel between the base station and UE (i), which changes over time due to Doppler shifts and mobility. The parameters α_l (t) represent the gain of the l-th path at time (t), and ⅎb{a}(θ_{T,l}(t)) and $a\left(\theta_{R,l}(t)\right)$ \) represent the array response vectors for the transmitting and receiving antennas, respectively. Wireless channels are dynamic and time-varying due to mobility, fading, and Doppler effects. This term models these dynamic changes, making the problem more realistic.

$$H_{i,r,d}(t) = \sum_{l=1}^{L} \alpha_l(t) a\left(\theta_{T,l}(t)\right) a^H\left(\theta_{R,l}(t)\right)$$

4.7 Energy Harvesting Model

This equation models energy harvesting for UE (i), where ($P_{i,r,d}^{allocated}$) is the power allocated to the UE i, RU r and distributed unit d, and $E_{harvested}(i)$ is the power harvested from renewable sources (e.g., solar energy). Energy harvesting is becoming a critical aspect in modern wireless networks to make them green and sustainable. By incorporating harvested energy, UEs can operate without solely relying on grid power.

$$P_{i,r,d} = P_{i,r,d}^{\text{allocated}} + E_{\text{harvested}}(i)$$

Combining all the above, the final multi-objective optimization problem} becomes:

$$\begin{gathered} max(\ \alpha_1 \frac{\sum_i R_{i,r,d}}{\sum_i P_{i,r,d}} \\ +\alpha_2 \sum_i \log_2\left(1 + \frac{P_{i,r,d} H_{i,r,d}}{N_{i,r,d} + I_{i,r,d}}\right) \\ +\alpha_3\left[-\sum_i \frac{P_{i,r,d}}{\sum_j P_j} \log_2\left(\frac{P_{i,r,d}}{\sum_j P_j}\right)\right] \\ +\alpha_4 \sum_i SINR_{i,r,d}) \end{gathered}$$

5 Real world assumption on predictability

In practice, several factors make the prediction of system performance more challenging. These include dynamic channel conditions, mobility, interference, and varying network load. To model these more realistically, the following real-world assumptions are added: The channel matrices, denoted by (H) for both MiMo and mmWave systems are time-varying, reflecting real-world channel fading and Doppler effects. The dynamic nature of the wireless channel is crucial for accurate predictions of system performance.

$$H_{i,r,d}(t) = \sum_{l=1}^{L} \alpha_l(t) a\left(\theta_T, l(t)\right) a^H\left(\theta_R, l(t)\right)$$

Where α_l (t) represents the gain of the l-th path at time t , and $a\left(\theta_T, l(t)\right)$ and $a\left(\theta_R, l(t)\right)$ are the transmit and receive array response vectors, respectively. These variations reflect Doppler shifts and UE mobility, affecting the predictability of the system's performance. Interference depends on the power allocation to other UEs and the beamforming vectors, which vary in real-time due to changes in UE behavior, the network environment, and dynamic load conditions. Interference for UE (i), RU r and distributed unit d is modeled as:

$$I_{i,r,d} = \sum_{j \neq i} P_j \left|H_{i,r,d} w_j\right|^2 \left(1 + \alpha\left|H_{i,r,d} w_j\right|^2\right)$$

Here, interference varies based on the beamforming vectors and UE-specific channel conditions. Many wireless devices are now designed to harvest energy from renewable sources. Energy harvesting for UE (i) is modeled as:

$$P_{i,r,d} = P_{\text{allocated}} + E_{\text{harvested}}(i)$$

This assumption allows the system to be more sustainable, where UEs can leverage harvested energy to supplement their allocated power. Network load, represented by the number of UEs and their data demands, varies throughout the day. This variability impacts power and bandwidth allocation decisions, making the system's behavior less predictable. The goal is to maximize the weighted sum of EE , SE, UE, F, and SINR, while incorporating the real-world effects of dynamic allocation, interference, and energy harvesting.

$$Z = \alpha_1 \frac{\sum_i R_{i,r,d}}{\sum_i P_{i,r,d}} + \alpha_2 \sum_i \log_2\left(1 + \frac{P_{i,r,d} H_{i,r,d}}{N_{i,r,d} + I_{i,r,d}}\right) + \alpha_3 \left[-\sum_i \frac{P_{i,r,d}}{\sum_j P_j} \log_2\left(\frac{P_{i,r,d}}{\sum_j P_j}\right)\right] + \alpha_4 \sum_i SINR_{i,r,d}$$

The power allocation equation accounts for distance-based path loss and fading, allowing for a more realistic allocation where UEs farther from the base station receive more power. To account for distance and fading, the non-linear power allocation for UE (i), RU r and distributed unit d becomes:

$$P_{i,r,d} = \left(\frac{d_{i,r,d}}{d_0}\right)^{\gamma} \left(\frac{1}{1 + \alpha \left|h_{i,r,d}\right|^2}\right)$$

Optimizing the SINR for each UE by adjusting the beamforming vectors based on the channel matrix. The ZFBF equation is used to manage interference in real-time is:

$$w_{i,r,d} = \left(H_{i,r,d}^H H_{i,r,d}\right)^{-1} H_{i,r,d}^H$$

Where ($w_{i,r,d}$) is the beamforming vector for UE i , RU r and distributed unit d. This optimization cancels interference, thus improving SINR. This equation accounts for the interference each UE experiences from other UEs, critical in multi-UE networks. Proper interference management ensures system efficiency. The interference term for UE (i) , RU r and distributed unit d depends on the power allocations (P_j) and beamforming vectors (w_j) for all other UEs:

$$I_{i,r,d} = \sum_{j \neq i} \frac{P_j \left|H_{i,r,d} w_j\right|^2}{1 + \alpha \left|H_{i,r,d} w_j\right|^2}$$

The dynamic channel model incorporates time-varying factors such as Doppler shifts and mobility, which are essential for accurately predicting system performance in real-world conditions. The dynamic channel model reflects real-world time-varying conditions. The channel for UE (i), RU r and distributed unit d at time (t) is:

$$H_{i,r,d}(t) = \sum_{l=1}^{L} \alpha_l(t) a\big(\theta_T, l(t)\big) a^H\big(\theta_R, l(t)\big)$$

The energy harvesting model incorporates renewable energy sources, making the system more sustainable. This allows UEs to operate with supplemental power from energy harvesting, reducing reliance on traditional power grids. To incorporate renewable energy sources, the power allocation is updated as follows:

$$P_{i,r,d} = P_{\text{allocated}} + E_{\text{harvested}}(i)$$

6 RESULTS

6.1 Simplified system model

Figure 1 shows the total throughput comparison for different number of UEs between three optimization algorithms (interior point, SQP and active set). The throughput results are varying greatly among UEs, which could be justified due to different factors explained in the presented Model. UE 5 shows a very high peak throughput for any optimizations. The reason for this increase in throughput is that there are good channel conditions for the UE. The channel gain (G_i) of this UE is likely to be large, therefore experience significant SINR. Moreover, the power for UE 5 may be set higher because of being a priority UE during optimization. It can be seen that all the three optimizers SQP, interior point and active set provide similar throughput for this UE implying that the optimization algorithms are committing resources to those UEs whose channel is better or gain is higher as per the system model. The results for UEs 1-4 and 6-10 show an up and down in throughput in the different methods. This interference is also higher for these UEs and this can justify the spread in the throughput between them. The interference from other UEs considered in Model 3 would affect their SINR and it is likely that the effect of beamforming (Zero-Forcing Beamforming in our case) cannot completely suppress this interference. The optimization techniques are trying to make trade-off between UE priority and fairness, however, noise predominates in the above mentioned UE ranges, thus different throughput performance can be observed. From these results, it could be supposed that there are cases for which interference control does not work so well even under the condition of more emphasis on power allocation and bandwidth.

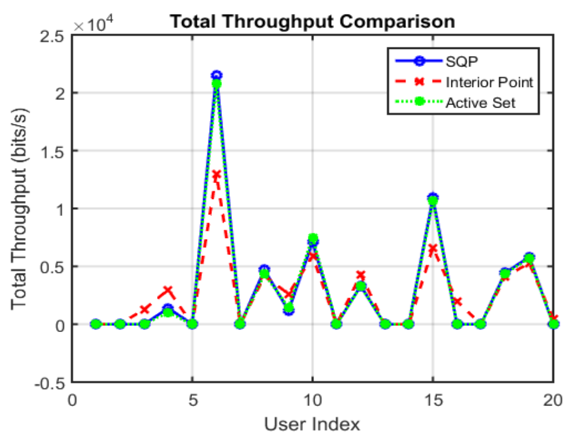

Fig.1: Throughput allocation among several UEs using three algorithms: SQP, active set and interior point.

The average throughput of UEs 11-20 is very low with some UEs having throughput close to zero. This can also be due to the unfavorable channel conditions, as these UEs could have lower distance from the base station or suffer high path loss according to (2) that matches with the mmWave path-loss formula. The role of the number of transmit and receive antennas, as characterized in Model 3 is apparent for the provision to manage such challenging channel conditions. Even though the optimization algorithms is devoted to power and bandwidth allocation they still experience high interference and low SINR. The low throughput for these UEs indicates that system performance decreases operating with poor channel conditions. Compared to the other two algorithms SQP maintains throughput superiority. Non-linear optimization problems are efficiently solved using SQP, making it a good choice for complex models such as MIMO and mmWave. The approach seems to do a good job in balancing power control, interference avoidance and UE ordering given the stable performance averaged over most UEs. On the other hand, the interior point method has a behaviour similar to SQP but with small differences for UEs 1 - 5. This approach is effective when optimizing problem size and may not be as effcient with respect to SQP in same-interference level and UE fairness based scenarios. While active set method is successful in specific situations, it suffers from more performance variability. It faces difficulties in controlling the trade-offs among fairness, throughput and power allocation under interference especially for those UEs with relatively worse channels. The number of the transmission antenna N_t and the number of receive antenna N_r have a crucial impact on the performance of this system. These parameters greatly affect the SINR and throughput calculations. In MIMO case, the channel capacity can be increased and the interference between signals can be reduced by increasing the number of antennas (antenna effect). UEs with better antenna condition should, in general, expect higher throughput (especially when the system utilizes beamforming to aim the signal toward the target UE and suppress interference; e.g., Zero Forcing).

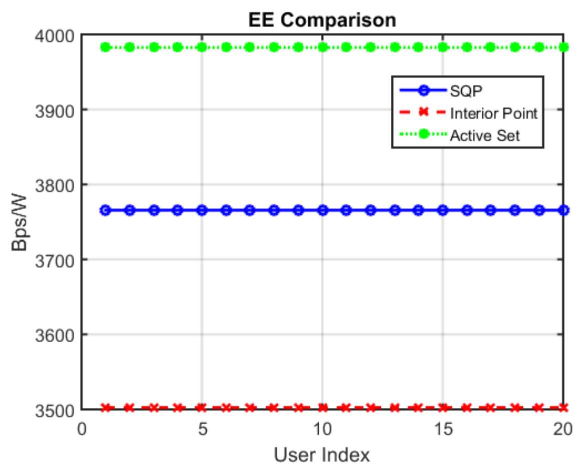

Fig.2: EE comparison among several UEs using three algorithms: SQP, active set and interior point.

Figure 2 shows the EE comparison of three optimization methods (SQP, interior point, and active set) for 20 UEs. It can be seen that for all of the four algorithms considered (SQP, interior point, active set), the EE is approximately constant across the 20 UEs. The EE values are around 3500 Bps/W-4000 Bps/W and do not significantly vary amongst the UEs. Though the total throughput (as evident from the "Total Throughput Comparison") fluctuated considerably among UEs, the EE seems a lot more stable. It indicates that the optimization techniques are actually balancing the throughput and power efficiently over the set of radios. The constant EE value means that the amount of power allocated to all UEs is proportional to their achieved throughputs, which indicates that the network operates very efficiently. Another important observation is that we have almost the same EE value across all UEs in case of the three optimization algorithms – SQP, interior point and active set. This implies that all the three methods perform similarly from an EE perspective on account of the static power allocation model which makes the bahaviour of the EE profile easy to grasp for each UE. These results suggest that the network is not too sensitive to the choice of optimization algorithm to reach good levels of EE. The manner in which power is assigned to the UEs affects EE. It is necessary to be able to perform efficient beamforming and interference suppression in MIMO and mmWave systems in order to reduce energy consumption. The constancy of the EE shows that the three proposed algorithms are converging toward optimal power allocation and that each can proportionally allocate power to UEs with their channel condition and throughput. The channel condition channel gain G_i, interference $I_{i,r,d}$ and noise factor $N_{i,r,d}$ are important links for throughput and power allocation. The convergence of EE for all considered optimization approaches indicates that there are consistent channel conditions experienced by UEs as implied from random initialization or the deployment of UEs across a lattice only. The system limited by maximum power and bandwidth. Because the optimization is on maximizing and suppressing throughput and power respectively, it's possible the two approaches will balance each other respectively to find some kind of sweet spot in EE. Under such limitations, the optimization algorithms could converge to similar solutions that satisfy the desired QoS levels and EE. The variety of antennas in MIMO system can affect SINR and the throughput. Contrary in the EE case the Antenna Gain does not have that much influence in this environmental (probably due to optimazation algorithms setup for power consumption and throughput balance rather than maximum SINR of a single UE). Subsequently, path loss in mmWave system is high, because of its high frequency, which further increases as UEs move away from the base station. In Model 3 the total path loss is taken into account but as EE represents a ratio of Total throughput to total power, it seems that the effect of path loss is considered uniformly for all UEs. The consistent EE values of UEs indicate that the system is managing to deal with these path losses and interference, such that good power utilization behavior persists without significantly sacrificing throughput. In both MIMO and mmWave systems, interUE interference practically degrades throughput. The closeness of the EE values also suggests that the schemes are addressing interference well among different UEs. Further, the fairness term in the optimization guarantees that power is shared equally preventing one UE from using excessive power, hence balancing and energizing the system. However, SQP has proven to be a convenient way of solving non - linear optimization problems, especially MIMO and mmWave systems. The ets of similar ees towards the others indicate that it can balance throughput and power consumption effectively. In addition, interior point This method achieves similar EE as SQP. It is more of a general technique that can be applied to larger problems, and it seems to do a great job here at optimizing the EE amongst UEs. On the other side, active set also gives very close EE values as the other two methods. The results for active set show that, though it is widely employed for problems with sparse constraints, EE-wise it performs similar to the rest. This demonstrates that the constraints in the system are not at too much sparsity level, and all three methods contribute to optimizing EE in the system similarly.

1.1 Predictability with dynamic allocation

Figure 3 shows the Data Rate characteristics of three optimization algorithms SQP, active set and IP for 10 UEs. The results indicate how each of the algorithms deals with the multi-objective optimization problem of tradeoff between throughput, UE fairness and energy efficiency in a time varying network environment. The performance of SQP is generally good for all the UEs with medium data rates (about 5 -9 Mbps). This stability is characteristic for the SQP method, where it usually converges kind of slowly in a feasible point and bring no attention to maximize the performance of each UE. S QP addresses non-linear optimization problems, an approximation of the problem into a quadratic subproblem is used and that works perfectly when the system behaves smooth, no dynamic interference. However, moderate performance of SQP is in a certain sense the result of losing dynamic capability. The algorithm does not well account for the unique signed channel characteristics (e.g., path loss, mobility and interference from other UE) experienced by a given UE. It does not therefore maximise data rates for those UEs with the best channel or seek to achieve maximum performance where channels allow "Using Encoding maximum throughput". Moreover, SQP is less adaptive to the UEs' interference situation and finally attains a uniform but not good resource assignment in dense UE or interference-limited scenarios. The performance of the active set optimization approach varies remarkably. Some of the UEs, such as UE 3 and UE 8 achieve significant data rates (up to 10 Mbps) while the others, for example UE 4 and UE 9 have much lower rates. active set is good in the fairness since weak channel condition UEs(i.e., a high path loss) receive more resources. This adaptive change causes different UEs to experience variable data rates. But there is a downside to such adaptive shape-shifting. The fluctuations suggest that in active set unfairness may be made worse because of a focus on fairness which causes subscribers with poor channels to become slightly over-resourced, and those with good channels under resourced. Additionally, the interference management is a problem in multi-UE cases where it is possible that the approach will not completely cancel out the interference and result low performance for UEs at hotspots. The high susceptibility to interference leads to a low uniformity in data rate allocation among UEs, as observed from the large variance in UE data rate between high-rate and poor-SINR. It can be seen that the interior point method performs better and more gradually than active set, presenting incremental data rate and peaking at around 11 Mbps for UE 9. It was designed for large-scale optimization problems and works well with the trade-off of multiple constraints over UEs. interior point targets a global system performance optimization maximizing total throughput, rather than locally optimal UE performance, which explains its different behavior when compared to the previous studies in terms of fairness. Interior point provides worse peak data rate for an individual UE than active set, but it gives the same good average data rates. The approach trades off peak performance for overall system efficiency. The relatively constant data rates indicate that the interior point is working to give consistently good performance, but not seeking the maximum possible performance for each UE. Advanced Active UE Selection can also achieve a stable interference management and dynamic adaptation in dynamic environments but it does not have the same "dynamic" responsiveness than active set to certain UE requirements.

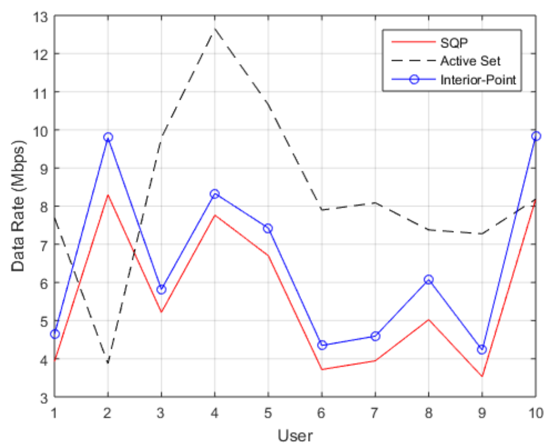

Fig. 3: Data rate comparison among several UEs using three algorithms: SQP, active set and interior point.

The disparities in performance are to be attributed to the fact that each optimisation algorithm attempts to solve the problem of trading off energy and spectral efficiency as well as UE fairness in a different way. The large fluctuation of active set is because it adapts schemes of resource allocation according to current channel state and emphasis on fairness. While this results in those UEs acquiring higher data rates due to an increased channel quality, the same co-UEs may not receive QoE due to the lack of consistency introduced by a larger number of MUs transmitting data. In contrast, SQP can provide more robust linkage but its performance comes at the expense of insufficiently maximizing the data rates of individual UEs. The conservative nature of the method in solving the optimization problem hinders its high performance under dynamic environments involving pronounced interference and channel variation. Finally, interior point not only returns a stable and linearly consistent solution for all UEs, but also optimizes system throughput globally. But it sacrifices individuals' peak performance to keep them under capacity and latency simultaneously, which is more appropriate for large scale systems with multi constraints.

1.2 Real world assumptions

Figure 4 shows the SINR of 10 UEs with three optimization algorithms for wireless communication network; SQP, active set, and interior point. SINR values for UEs 1-4 and 6-7 are generally low, most likely due to very high interference from neighboring UEs as well as some adverse channel conditions. For these cases, the SQP algorithm (shown with the red line) performs best as it keeps the SINR at a relatively high level of roughly 0.4–0.5. The fact that the same number of the SQP method manages interference-and power allocation of these UEs more efficiently that if they are served with a superior priority, keeping more justice among UEs, despite maximal spectral efficiency. On the other hand, active set (black line) is able to maintain the SINR level as well, but only with some oscillations, which means that it does not perform well with UEs having high-interference. For these UEs, interior point (blue line) has the largest degradation, which suggests that this approach is least able to reduce interference and adapt to time-varying channel conditions, both of which are essential in multi-UE scenarios. The mathematical model for SINR shows that interference is a key reason for the lower SINR seen by these UEs. Since the interference term ($\sum_{j \neq i} P_j \left|H_{i,r,d} w_j\right|^2$) directly affects the SINR, the optimization algorithms have to strike a better balance by distributing the power allotted among the UEs to reduce this interference. Because SQP is an iterative optimization method, it can adapt to real-time changes in the power allocation, and is thus more effective in optimizing the SINR under these circumstances. Notably, UE 5 has a much higher SINR (approximately 1.8), particularly under active set optimization. This implies that UE 5 enjoys more favorable channel conditions, maybe due to a more favorable channel matrix ($H_{i,r,d}$), which corresponds to larger beamforming vector ($w_{i,r,d}$) and subsequently higher SINR. Since this UE has good channel states, optimization algorithms deliver most power to this UE. This is theoretically justified by the UE prioritisation introduced in the optimisation framework which prefers UEs assigned high channel gains and low inter-UEs interference. Similarly, SQP and interior point also convey fairly high SINR values (17.34 and 17.98 dB respectively) for UE 5; still, active set leads as better. Also, when a UE is on the corner of good channel conditions, both make use of UE priority cum beamforming optimization so that the same UE gets the best SINR for this region, indicating that active set is especially beneficial for these UEs. SINR values for all active UEs Under interior point optimization SINR values for UEs 8-10 are low in a absolute sense especially for mmWave systems, path loss is high, and increases with distance, therefore, these UEs may be experiencing higher path loss. In mmWave path loss model, UEs situated farer from the base station or towards higher (Rayleigh) blockage will experience higher path loss and SINR. For these UEs, SQP and active set do retain a certain amount of SINR, but is lower than the rest, indicating that they may face significant interference from other UEs. This latter is particularly expedient if we consider the interference term in the SINR formula, ($\sum_{j \neq i} P_j \left|H_{i,r,d} w_j\right|^2$), where high interference from nearby UEs reduces the effective SINR for these UEs. Moreover, the beamforming optimization is not performed very well for these UEs, for example in graph, the SINR does not increase much, even equipped with SQP and active set The dynamic channel conditions modelled in the paper, can expose these UEs to additional challenges resulting in the observed lower SINR. As expressed by ($H_{i,r,d}(t)$) the channels are time-varying, which results in UEs experiencing a fluctuating SINR as a result of mobility effects, Doppler-shift, and interference from other UEs

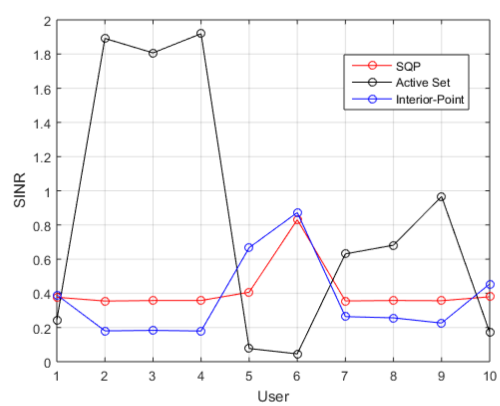

Fig. 4: SINR comparison among several UEs using three algorithms: SQP, active set and interior point.

Figure 5 illustrates the SE achieved by 10 UEs on a wireless communication network, using SQP, active set and Interior- Point as algorithms for optimization. To get a comprehensive understanding of the outcome, we need to compare them with the mathematical models and optimization framework of power division beamforming strategies interference control funding discussed in Section 5 – which applies to both MIMO (Multiple Input Multiple Output) systems and mmWave (millimeter wave) frequencies. In the regions where SSE has a moderate but high value, we can see that SQP (represented by the red line) always stands at this level, meaning it is increasingly satisfying power allocation over beamforming strategies among UE 1–4 and 6–7. Presumably as a result of its efficient use these two fields are together conspicuous enough to yield relatively broad spectral improvements. The UE 5 and UE 6 getting greater SE than anyone else belong to the active set group. active set (black line) But for other people, their performance sways more often; this shows that active set's handling of interference is less efficient or that it may not always be as good as SQP in terms of mode-switching power allocation and beamforming strategy adjustments. It seems probable, therefore, that in choosing UEs with better channel conditions, active set is responsible for a higher SE on the part of those with good conditions yet unfavorably performance among its members. The poorest performing consistently of the three is interior point (the blue line). Its SE intermittently tends to hover around 5–6 bits/s/Hz for different UEs. This means that interior point has more difficulty in allocating resources optimally under dynamic conditions. It shows a lower SE than SQP and active set, particularly when there is interference. Thus from the perspective of SE, SQP performs better With better regard to both division of power and treatment of interference, its UEs gain higher spectral efficiencies. In active sets, UE 5 has a particularly High SE Value (The black line), which peaks out at 12 to 13 bits/s/Hz. It is probably because of UE 5's favorable channel conditions, and this is what active set algorithm makes use of in order to drive up his SE. The model of optimization gives this UE the most consideration, with even more power across sites being directed towards him and a fine-tuned beamforming method (beam capture) used to improve transmission quality. However, even if it looks to be essential for SQP's successful operation of treating all UEs fairly (as well as other such things), it is hardly anything like that for individual UEs, at least not with the forcefulness exhibited towards them by active set. For UE 5, however, interior point shows poorer SE. Their method does not perform well when it comes to such efficient resource allocations under the present conditions. And this is also consistent with the paper's optimization framework, which is designed to maximize net Spectral Efficiency while ensuring fairness among UEs and minimizing interference. For UE 5, the methodology that the workpaper pursues has turned out to be no worse than with active set's methods, that is higher SE values. Active set shows a significant reduction in SE for these UEs, which indicates that the algorithm isn't able to manage interference effectively in this case. As active set is more designed for higher priority UEs (those with good channel conditions), it doesn't work so well with people in inferior conditions. Compared to the other algorithms, the performance of interior point algorithms seems to be the worst. These lower SE values imply that the interior point algorithm is neglecting details such as channel conditions and interference, both of which are critically important in a real-world system where you need to maximize spectral efficiency. This is true in particular for the Southeast Asian region, as reported by those 3GPP repeaters--which are installed at numerous points before and after every WCDMA base station.

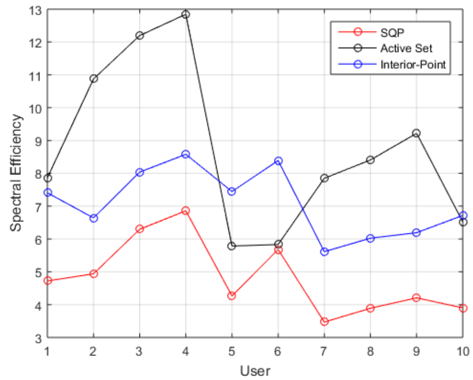

Fig. 5: Spectral efficiency comparison among several UEs using three algorithms: SQP, active set and interior point.

7 CONCLUSIONS

In this paper, we investigated the deployment of MIMO and mmWave communications in next generation systems. It suggests a multi-objective optimization system to improve the EE, SE and UE fairness in dynamic network conditions with robustness. The paper also considers realistic assumptions, such as time-varying channels, mobility and interference levels as well as energy harvesting that capture the behavior of MIMO and mmWave systems in real-world environments. The work also discusses the performance of three optimization methods- SQP, active set and interior point with respect to power allocation, beamforming optimization and managing interference. SQP achieves the best performance and it is a solid way to solve the problems under uncertainty and interference. AS delivers the worst results in high interference and with less optimal channels, and IP is the least efficient when UE fairness and interference management are important. The role of MIMO is highlighted because it is a key enabler for mmWave systems to satisfy the rapidly increasing capacity and data-rate requirements of modern communication systems. Combining these two technologies can improve system performance through spatial multiplexing and MIMO beamforming in case of the former, and wide bandwidth in the latter. With this common framework, the joint optimization of these technologies in the proposed approach substantially enhances the overall throughput and system reliability to accommodate for high requirements of next generation wireless systems.

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NONE

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