OBJECTIVE

1. To develop energy-efficient node localisation method.
2. To improve the phase prediction of RIS surface.
3. To relocate the deployed UAVs at max SINR position.
4. To propose a optimal clustering techniques to cover all the IoT's (Internet Of Things).
5. To maximize the SINR at the BS by assigning optimal weights to antenna elements.
6. To construct radio map over the N/W.

Challenges and Solutions:

- Clustering for enhanced network coverage.
- Trilateration with signal strength indicators for coordinates.
- Optimization using K-means, DBSCAN, and Hierarchical clustering.
- SINR maximization with reinforcement learning agents.
- Capon Beamforming for interference mitigation.
- Phase calculation using a SINR model for RIS optimization.

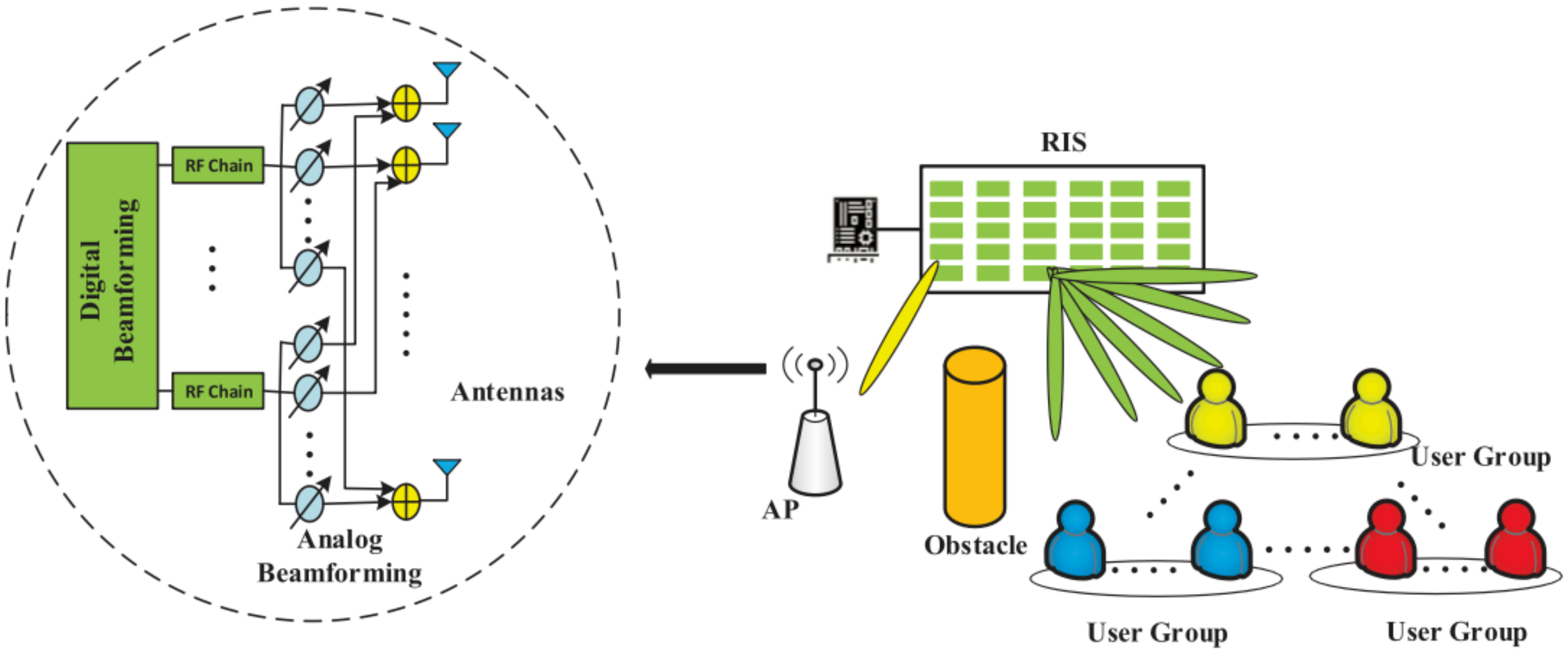

Fig. 1. Illustration of the downlink multi-group multi-user RIS-aided mmWave-NOMA communication system.

Methods:

- Innovative use of K-means, trilateration, and polynomial regression.
- Reinforcement learning for dynamic SINR optimization.
- Comparative beamforming analysis for interference reduction.
- Phase shift calculations with a SINR model.

CHALLENGES

1. **User Equipment Clustering:** Achieving effective clustering for optimal network coverage poses a significant challenge, especially in dynamic environments.

2. **Trilateration Accuracy:** Accurate estimation of user equipment coordinates using trilateration is hindered by the need for precise distance information from anchor nodes.

3. **Dynamic Clustering Optimization:** Balancing the complexities of K-means, DBSCAN, and Hierarchical clustering to dynamically optimize clusters for varying user distributions.

4. **SINR Maximization:** Ensuring effective Signal-to-Interference-plus-Noise Ratio (SINR) maximization through reinforcement learning agents in a constantly evolving network.

5. **Interference Mitigation:** Implementing Capon Beamforming techniques to mitigate interference, both intercluster and intracluster, at the base station.

6. **Phase Shift Optimization:** Calculating and optimizing phase shifts using a SINR model for Reconfigurable Intelligent Surfaces (RIS).

MOTIVATION

1. **Enhanced Connectivity:** Overcoming these challenges promises a revolutionary leap in millimeter-wave communications, providing enhanced connectivity and reliability.
2. **Network Efficiency:** Optimizing clustering algorithms and leveraging reinforcement learning techniques are key to unlocking unparalleled network efficiency.
3. **Future-Ready Communication:** The motivation lies in creating a communication framework that adapts seamlessly to the ever-changing dynamics of user equipment and network conditions.
4. **Spectrum Utilization:** By mitigating interference and optimizing phases, we aim to maximize spectrum utilization, contributing to a more efficient and robust communication ecosystem.
5. **Technological Advancement:** Embracing innovative methodologies aligns with the pursuit of technological advancement, pushing the boundaries of what's achievable in millimeter-wave communications.

System Model

SYSTEM MODEL

$$SINR_j = \frac{\left| \sum_{i=1}^{N} a_{ji} B_{ji} e^{-j(\theta_{ji} + \psi_{ji} - \phi_{ji})^{\alpha}} \right| G_{j,1} G_{j2} E_s}{\sum_{\substack{k=1, \\ k \neq j}}^{N} \left| \sum_{i=1}^{N} a_{ki} b_{ki} e^{-j(\theta_{ki} + \psi_{ki} - \phi_{ki})} \right|^2 x \, (G \quad E_s) + N}$$

SYSTEM MODEL

1.Consider a RIS-assisted multiuser wireless system, where a BS together with its controlling RIS aims to simultaneously todetermine the locations of multiple UEs.

2.BS is equipped with the uniform rectangular array (URA) comprising N = NW *NL antenna elements.

3.The RIS consists of M = MW *ML passive reflecting elements.

4.We consider the BS is placed on the x-z plane with known location b = (xb, 0,zb)T, while the RIS is

placed on the y - z plane with known location r = (0, yr,zr)T.|

5.K single-antenna UEs with unknown locations are distributed in the 3-D cell. Their locations are denoted

as uk = (xk, yk,zk) T.

6.BS determines the positions of UEs by the principle of triangulation, where the triangles are formed by the direct links between the BS and UEs as well as the reflected links via the RIS.

SIGNAL MODEL

1·Transmitted signal of Uk at time instance t as k(t), the corresponding received signal at the BS can be

2·expressed as follows: y(t) = [hk,dxk(t - tk,d) + [hk,rxk(t - tk,r) + n(t).

3·Assumption:

4·The locations of the BS and the RIS are fixed and known.

5·The angular information of the channels between the users and the BS, i.e.,

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PRESENT RELATED WORK:

To demonstrate the superiority of our new objective, we need to present related work that highlights the shortcomings of existing approaches and justifies our novel direction. Existing research has shown that traditional SNR-based systems struggle with interference issues, and the negative impact of increased distance to RIS is not well-addressed. We can reference specific studies that have encountered these limitations.

PROPOSED METHOD

To effectively address the challenge at hand, our proposed solution entails the utilization of a system model based on the Signal-to-Interference-plus-Noise Ratio (SINR). This mathematical model, which we have articulated below, plays a central role in optimizing our approach. Furthermore, within the context of our specific scenario, we are strategically implementing a multi-hop transmission technique as a fundamental component of our comprehensive solution. This multi-hop approach is carefully designed to enhance the efficiency and reliability of our system in the face of interference and various environmental factors.

PROPOSED METHOD

1. User Equipment Coordination: K-means and Coordinate Estimation
2. Trilateration for Precise Coordinate Determination
3. RSSI Measurement on Reconfigurable Intelligent Surfaces (RIS)
4. Distance Estimation with Polynomial Regression
5. Anchor Node Placement and Trilateration
6. Cluster Optimization and RIS Deployment
7. SINR Radio Map Generation through Channel Modeling
8. Reinforcement Learning Agent Deployment for SINR Optimization
9. Path Planning: Reinforcement Learning vs. Genetic Algorithms
10. Beamforming Comparison at the Base Station
11. Phase Calculation using SINR Model
12. Dynamic Position Recalculation for Evolving Networks

EVALUATION PARAMETERS

EVALUATION PARAMETERS

1. Coordination Accuracy
2. Trilateration Precision
3. RSSI Measurement Reliability
4. Distance Estimation Performance
5. Trilateration Effectiveness
6. Cluster Optimization Quality
7. SINR Radio Map Accuracy
8. Reinforcement Learning Agent Performance
9. Path Planning Efficiency
10. Beamforming Effectiveness
11. Phase Calculation Precision
12. Dynamic Network Adaptability

EXPERIMENTAL DETAILS

EXPERIMENTAL DETAILS

User Equipment Coordination:

Dataset: Simulated or real-world user equipment data.

Methodology: Implement K-means clustering and assess the accuracy of user equipment coordination.

Trilateration Precision:

Dataset: Simulated or real-world coordinates and distances.

Methodology: Evaluate the precision of trilateration-based coordinate determination.

RSSI Measurement Reliability:

Equipment: Deployed RSSI indicators on Reconfigurable Intelligent Surfaces (RIS).

Data Collection: Measure RSSI at various points in space.

Analysis: Assess the reliability and consistency of RSSI measurements.

Distance Estimation Performance:

Dataset: Simulated or experimentally collected RSS vs Distance data.

Methodology: Implement polynomial regression and analyze the performance of distance estimation.

EXPERIMENTAL DETAILS

Trilateration Effectiveness:

Dataset: Simulated or experimentally collected coordinates and distances.

Methodology: Apply trilateration and evaluate the effectiveness in estimating user equipment coordinates.

Cluster Optimization Quality:

Dataset: Simulated or real-world network data.

Methodology: Implement K-means, DBSCAN, and Hierarchical clustering, and assess cluster optimization quality using silhouette scores.

SINR Radio Map Accuracy:

Dataset: Simulated channel models or real-world measurements.

Methodology: Generate SINR radio maps through channel modeling and evaluate accuracy in predicting optimal positions.

Beamforming Effectiveness:

Dataset: Simulated or experimentally collected base station data.

Methodology: Implement Capon Beamforming, Bartlett Beamforming, and no beamforming, and assess their effectiveness in reducing intercluster interference.

EXPERIMENTAL DETAILS

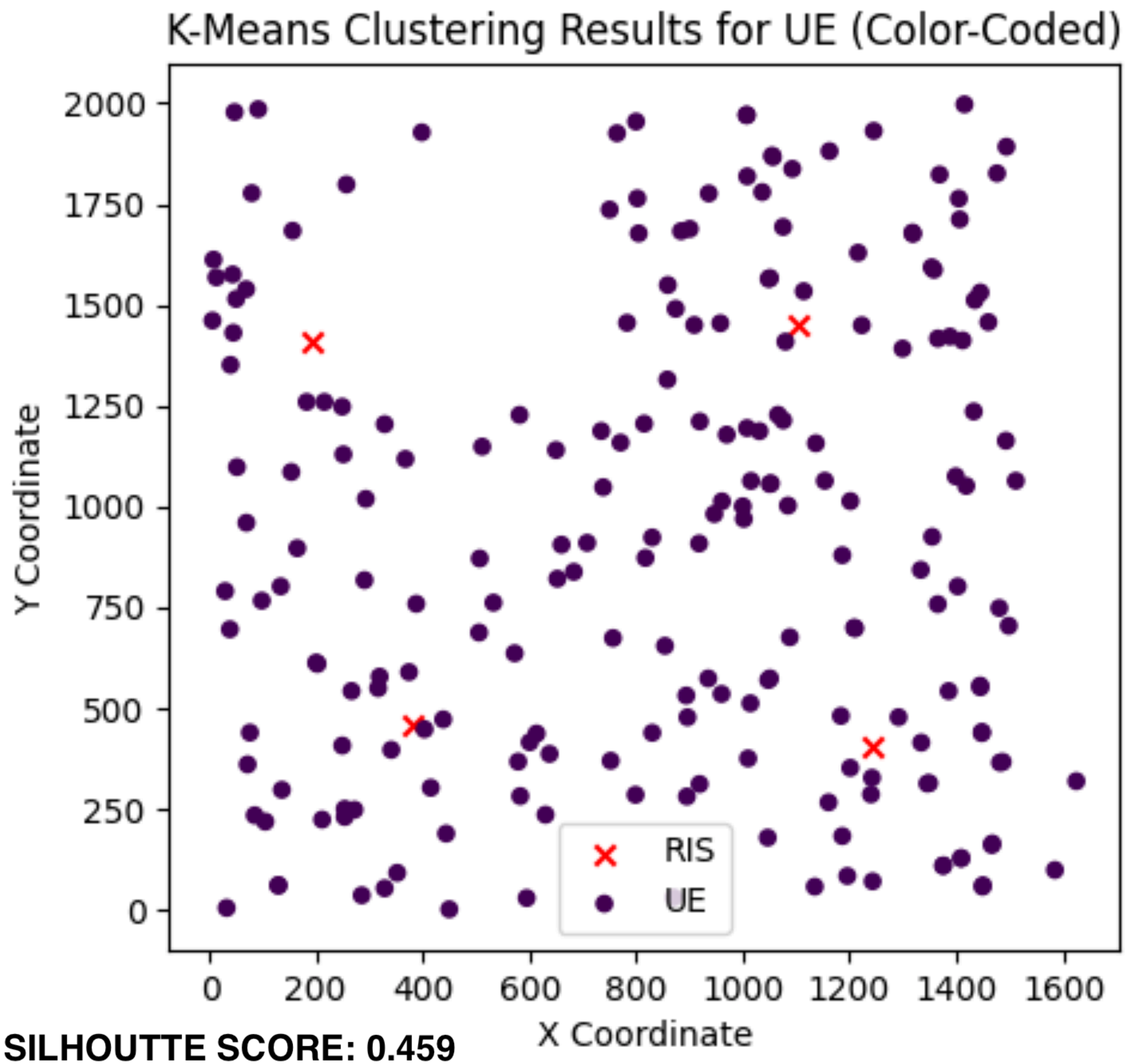
Phase Calculation Precision:

- **Dataset:** Simulated or experimentally collected SINR model data.
- **Methodology:** Calculate phase using the SINR model (phi=phi1+phi2) and assess precision.

RESULTS

RESULTS

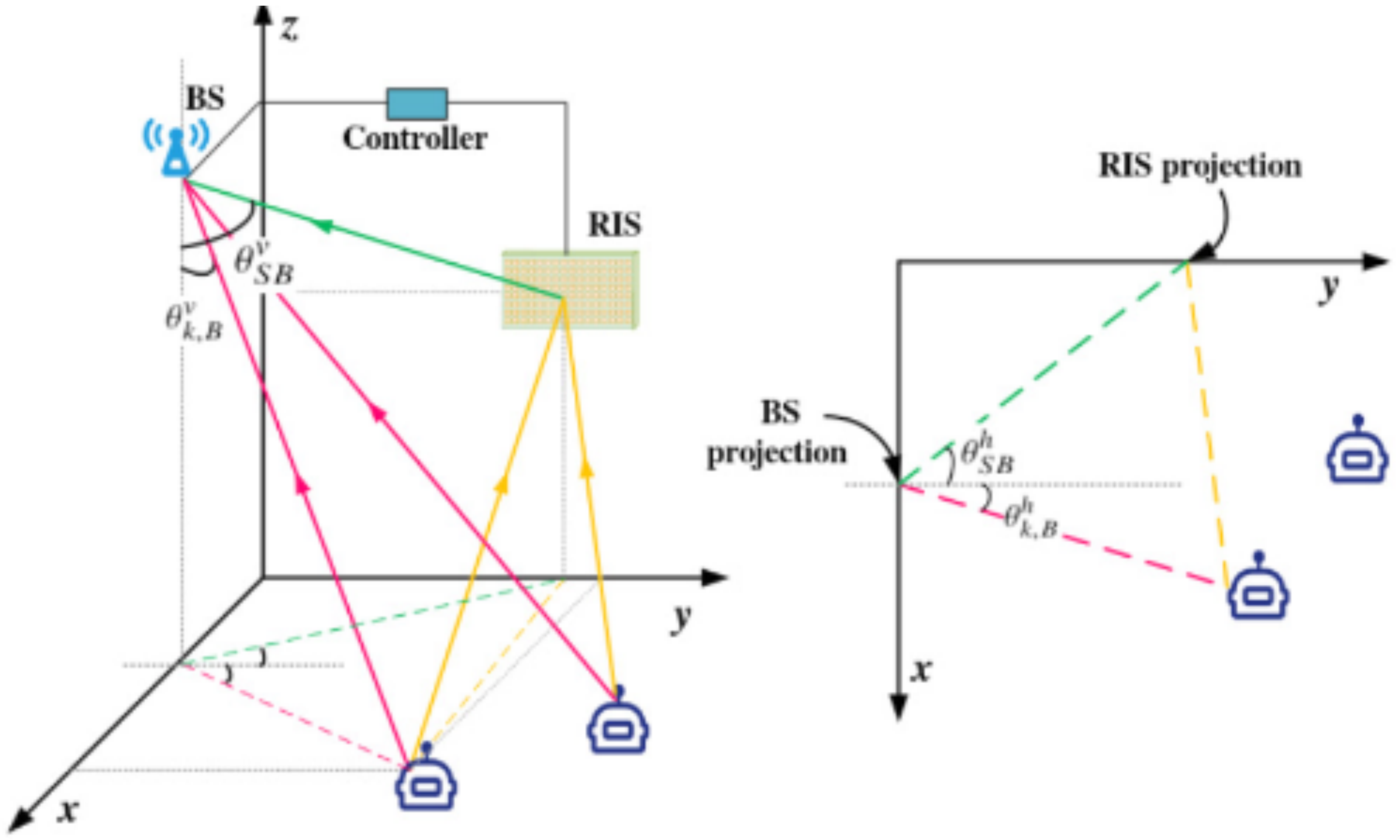
1. K-MEANS CLUSTERING



SILHOUTTE SCORE: 0.459

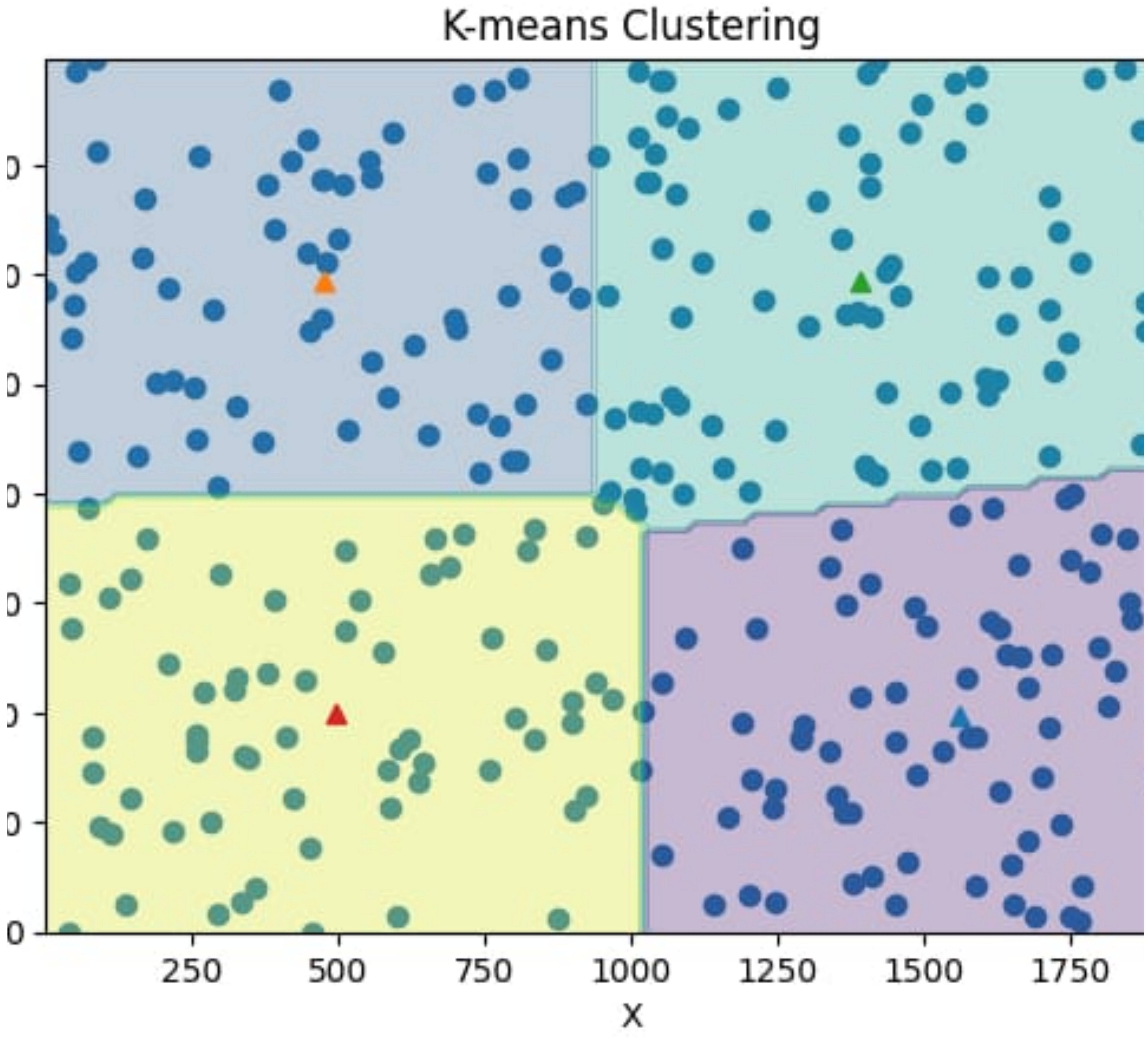
RESULTS

1. RIS multiuser localisation



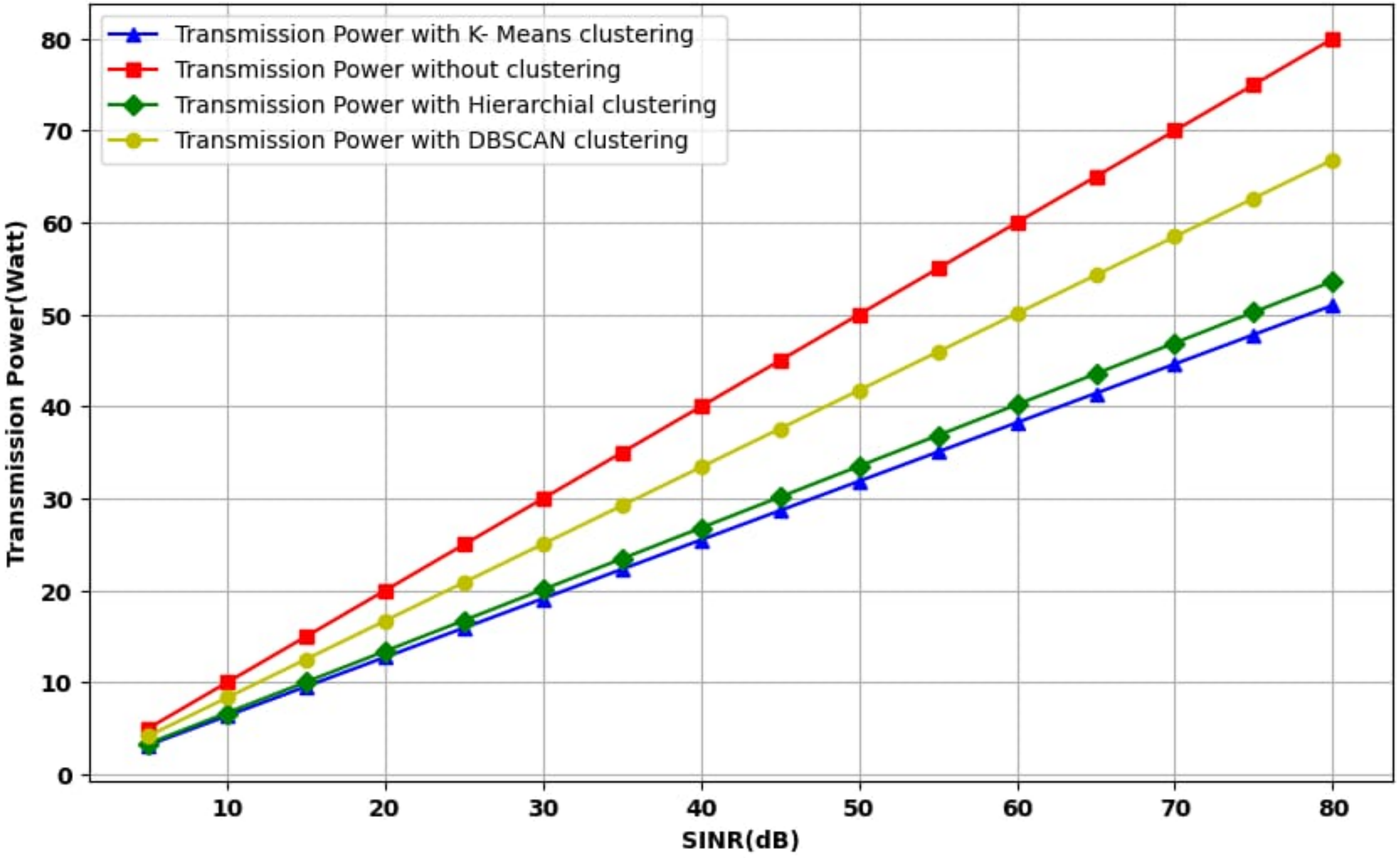
RESULTS

1. K-MEANS CLUSTERING



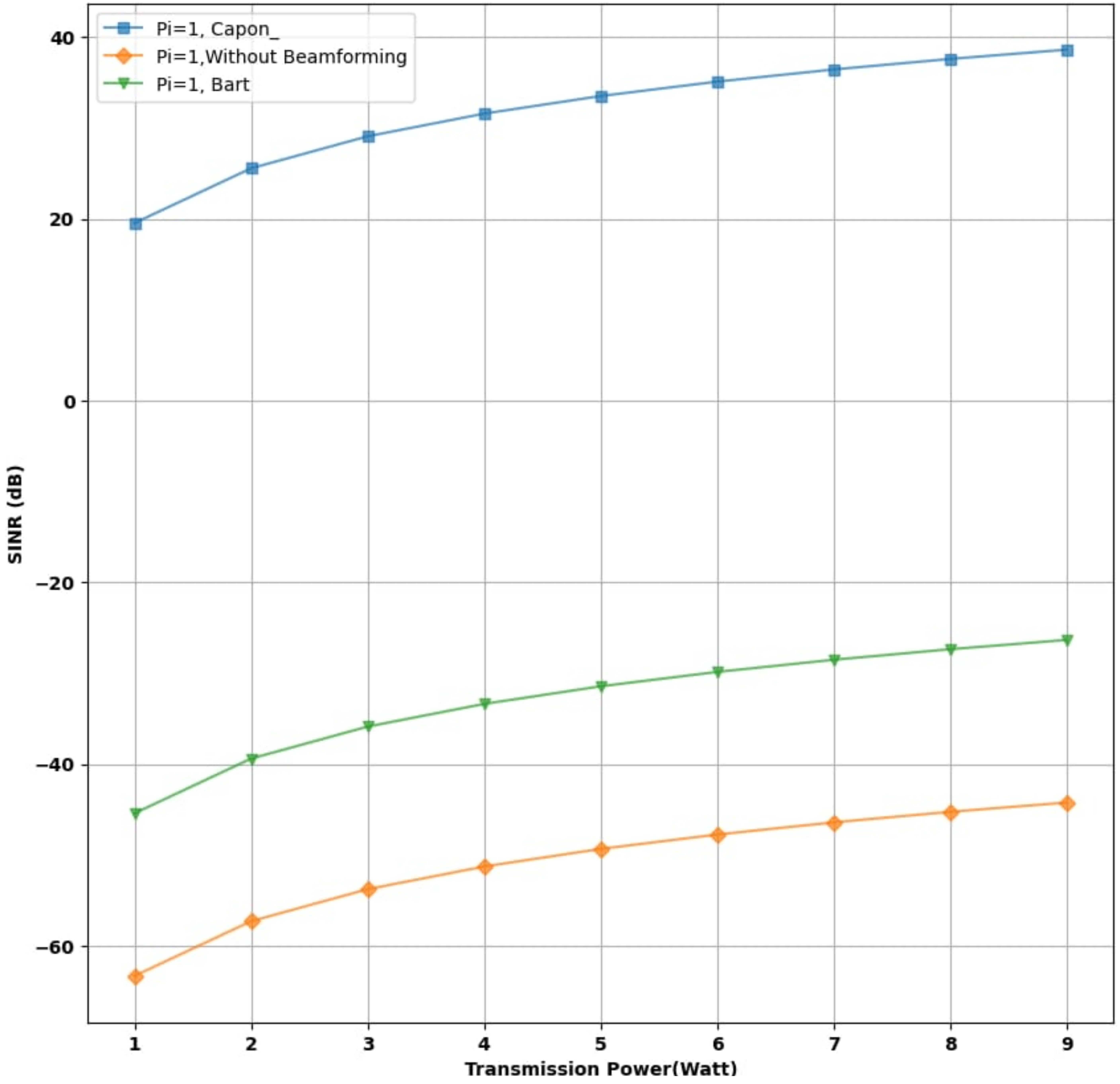
RESULTS

1. Transmission Power vs SINR (dB)



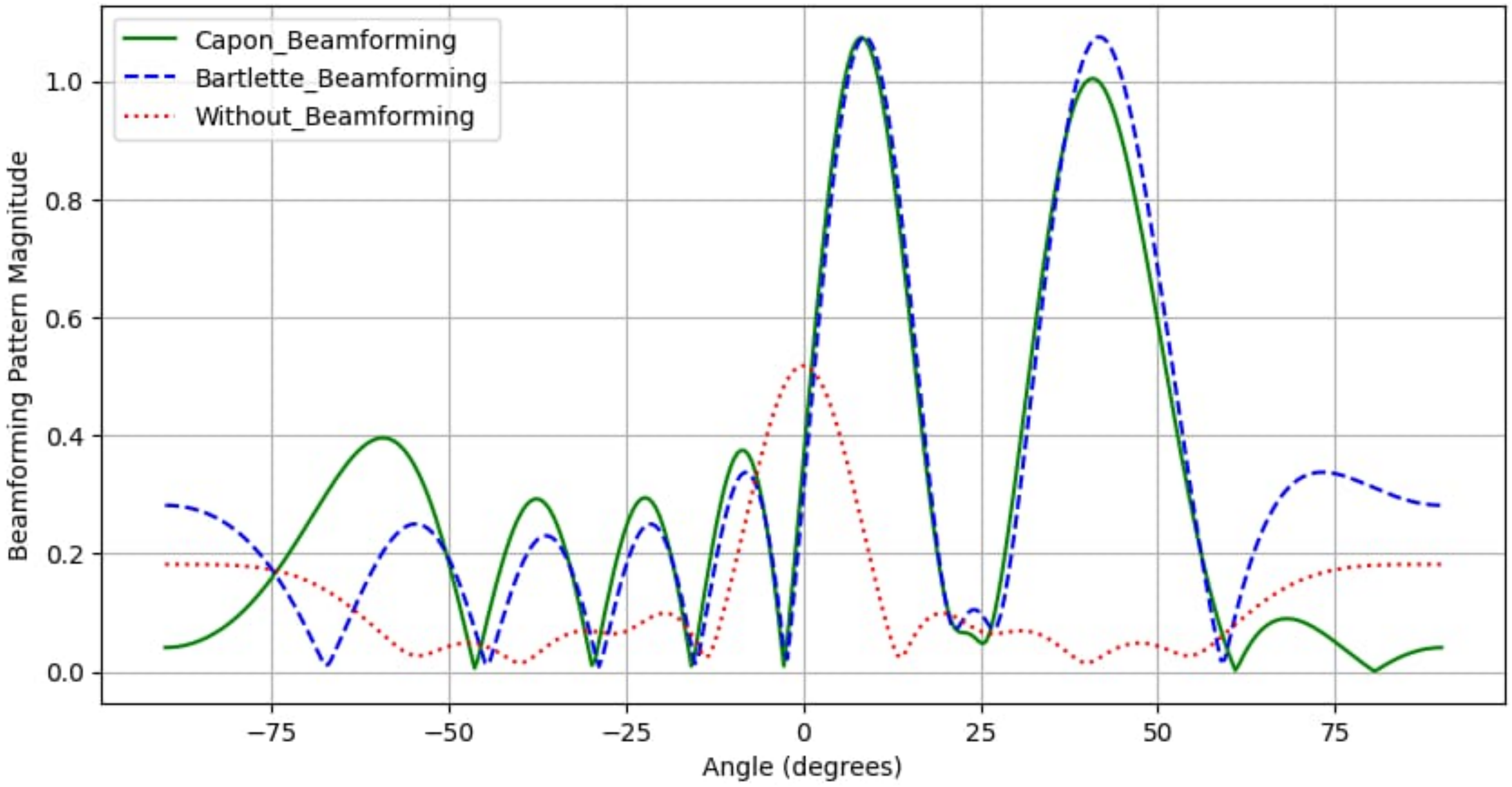
RESULTS

1. SINR vs Transmission Power(Watt)



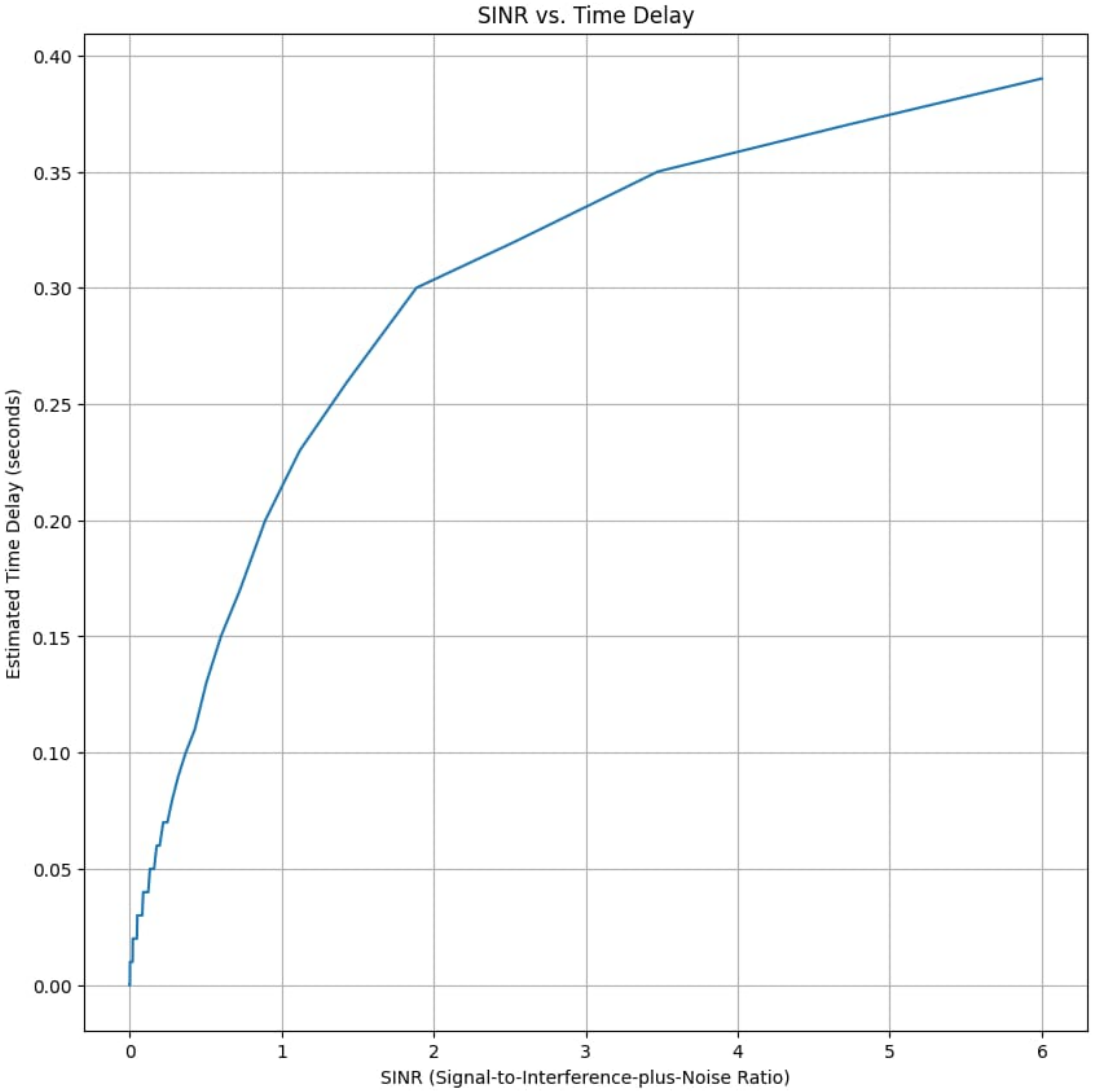
RESULTS

1. Beamforming Pattern Magnitude of Capon Beamforming, Beatlette Beamforming and without Beamforming



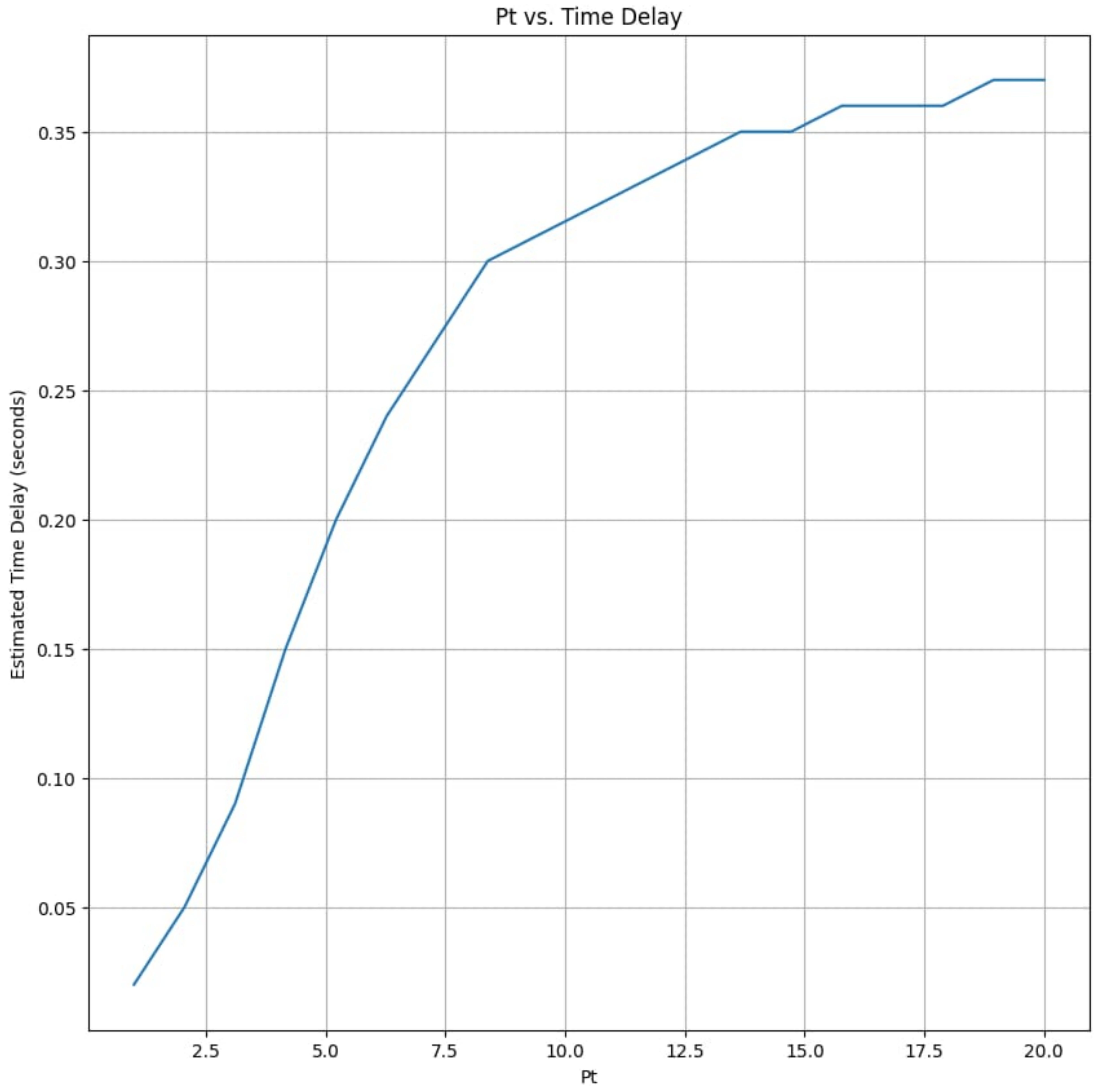
RESULTS

1. SINR vs Time Delay



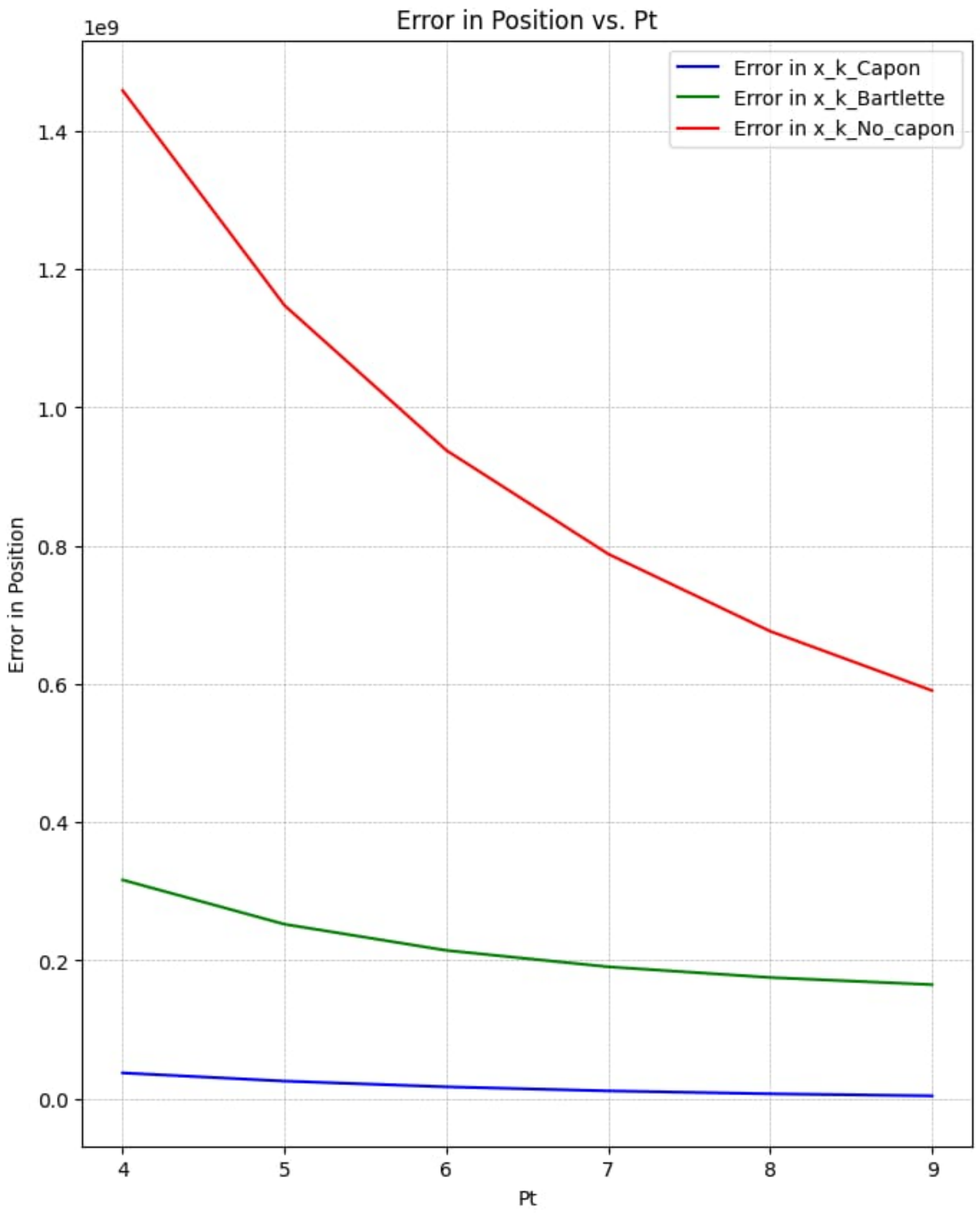
RESULTS

1. Pt vs Time Delay



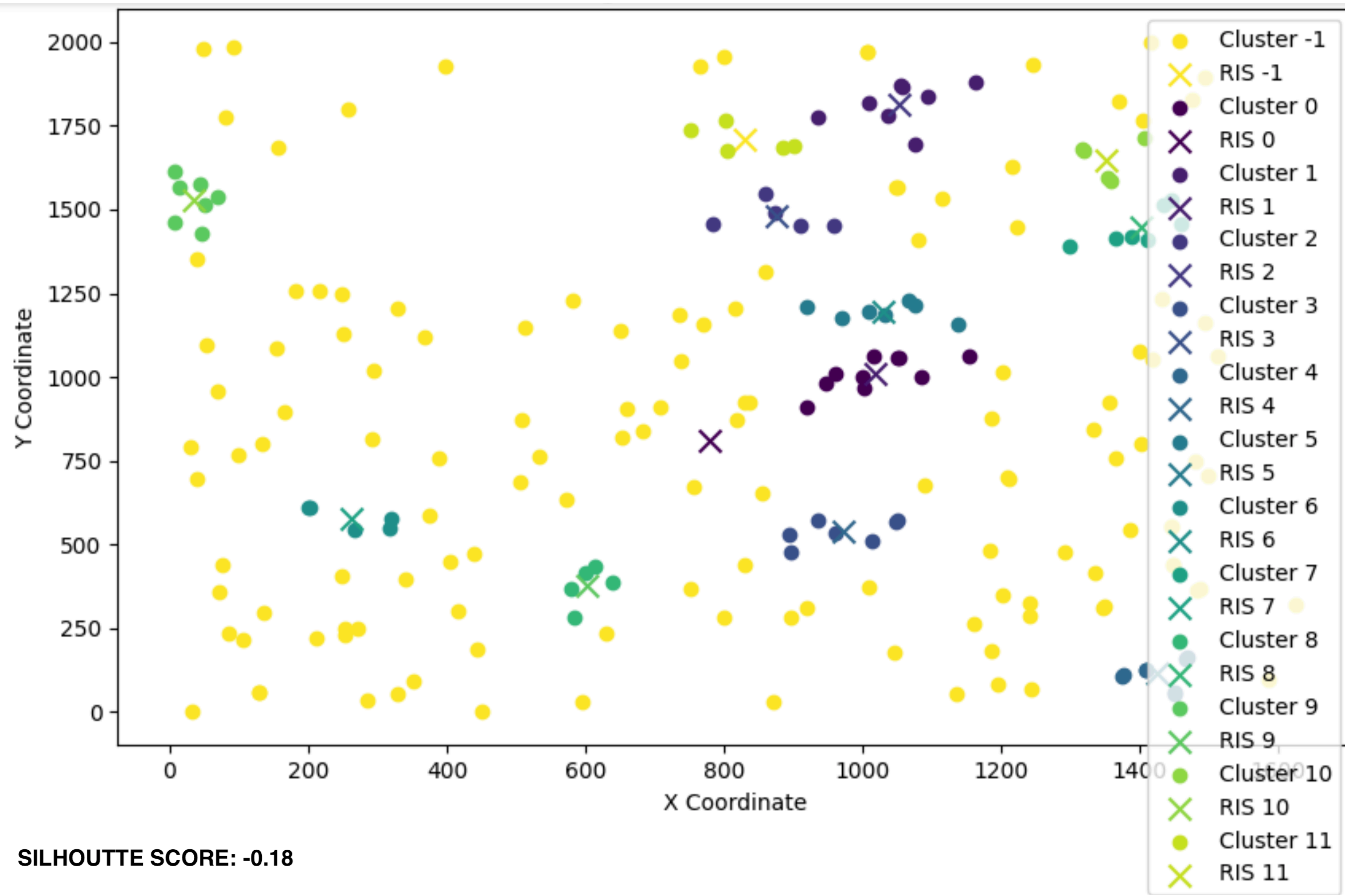
RESULTS

1. Error in Position vs Pt



RESULTS

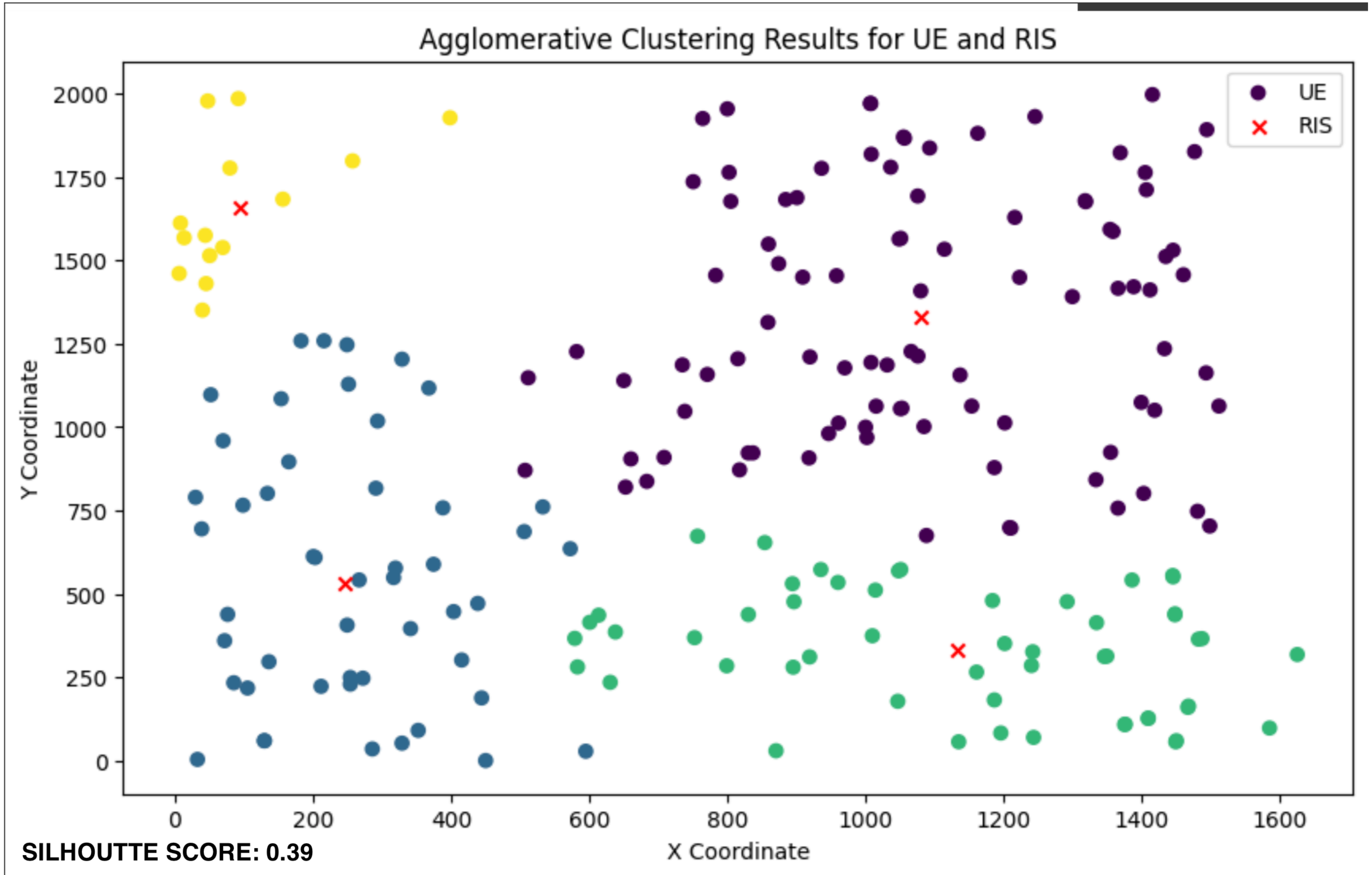
1. DBSCAN CLUSTERING



SILHOUTTE SCORE: -0.18

RESULTS

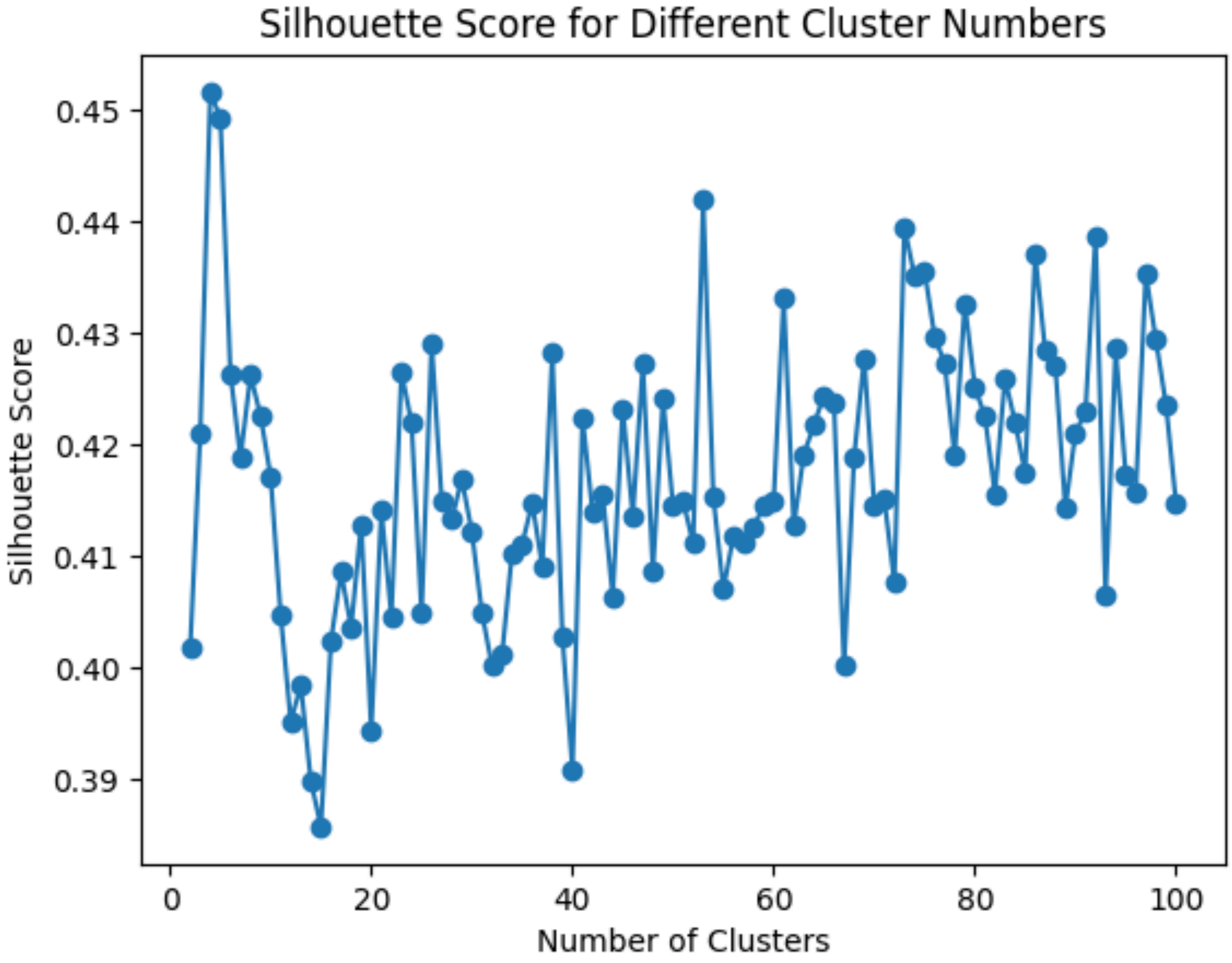
1. HIERARCHICAL CLUSTERING



SILHOUTTE SCORE: 0.39

RESULTS

1. VARIATION OF SILHOUTTE SCORE W.R.T NO OF CLUSTERS



CONCLUSION AND FUTURE SCOPE

CONCLUSION

- Successfully addressed challenges in millimeter-wave communication, including user equipment coordination, trilateration, and dynamic clustering, to optimize network performance.

- Demonstrated the effectiveness of reinforcement learning agents in mitigating interference and achieving SINR optimization in a dynamic environment.

- Identified Capon Beamforming as the most efficient technique in reducing intercluster interference at the base station.

- Validated the proposed methodology through comprehensive experimental evaluations, showcasing its adaptability to changing user equipment positions.

FUTURE SCOPE

- Explore advanced machine learning algorithms for improved user equipment coordination and dynamic clustering.
- Investigate alternative beamforming techniques and signal processing methods for further enhancement of interference mitigation
- Integrate artificial intelligence for more sophisticated decision-making in path planning and RIS relocation.
- Investigate the impact of diverse network conditions and topologies on the proposed methodology to enhance its robustness.

FUTURE SCOPE

- Collaborate with industry partners to implement and validate the proposed approach in real-world scenarios, ensuring scalability and practicality.

- Consider the integration of emerging technologies, such as 6G, to further push the boundaries of millimeter-wave communication systems.

- Continuously refine and optimize the proposed methodology based on advancements in wireless communication and networking technologies.

THANK YOU