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A Decision-Support Model for 6G IoT Beamforming via Tri-Objective Pareto Optimization

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Abstract

In today's world, the rapid advancement of 6G-enabled IoT networks has created high demands for energy efficiency, latency, and throughput. Existing research often publishes these performance metrics either in isolation or through bi-objective formulations, which cannot adequately represent the underlying trade-offs. This study introduces a tri-objective Pareto optimization framework for 6G IoT beamforming that simultaneously considers energy consumption, latency, and throughput. Using a real beamforming dataset, a Pareto analysis has been employed to uncover the empirical trade-off structure, and a surrogate regression model has been developed to approximate KPI interactions. Evolutionary optimization integration provides a smooth Pareto frontier and highlights clear operating zones under different IoT scenarios. The results reveal a strong nonlinear coupling among the three Key Performance Indicators and underscore the superiority of the proposed framework over previous single or bi-objective approaches. It will provide and help transparent and explainable decisions for beamforming configurations; this study is expected to establish a solid foundation for adaptive resource management in future 6G IoT systems.

Keywords

6G IoT Beamforming, Energy Efficiency, Latency Optimization, Throughput Maximization, Multi-Output Regression.

1. Introduction

The emergence of sixth-generation (6G) wireless communication is expected to revolutionize connectivity by enabling massive IoT deployments, ultra-reliable low-latency communication (URLLC), and highly energy-efficient networking (Hoque & Huq, 2025), (Nassar et al., 2025). These high requirements will place considerable demands on beamforming technologies, which will simultaneously deliver high throughput, minimize power consumption, and reduce latency (Ihsan et al., 2022), (Ahn et al., 2023). As the density of IoT devices will continue to grow, which in turn achieves a balanced trade-off among these conflicting key performance indicators (KPIs) will become increasingly complex (Elgarhy et al., 2024).

Most existing studies on 6G and IoT focus on architectural concepts, physical-layer simulations, or single-key performance indicator (KPI) improvements, such as enhancing spectral efficiency or reducing delay (Dilli, 2022), (Feng et al., 2025). Although these contributions provide valuable insights, they have often relied on simulated environments and failed to incorporate real datasets (Ananthanarayanan et al., 2025). More importantly, they do not provide a quantitative understanding of how energy, throughput, and latency interact simultaneously within beamforming systems (Krishnamoorthy et al., 2025). In the current literature also lacks a unified multi-objective optimization framework that can not guide practical design decisions in complex 6G scenarios (Alwakeel, 2025), (Qi et al., 2022).

To solve these gaps, this study provides a dataset-driven optimization pipeline for analyzing and improving 6G IoT beamforming performance. The proposed approach began with an empirical Pareto analysis to uncover the natural trade-off structure among the three key performance indicators (KPIs) (Kanani et al., 2025). A multi-output surrogate model trained using machine learning has been developed to approximate the input–output relationships (Ananthanarayanan et al., 2025). To efficiently explore the optimization space, the surrogate model has been integrated with the NSGA-II evolutionary algorithm. It has produced a dense and smooth Pareto frontier that represents optimal trade-off solutions (Krishnamoorthy et al., 2025).

The contributions of our work are threefold. Firstly, it provides real data analyses of 6G beamforming KPIs using real measurements rather than simulations (Kanani et al., 2025). Secondly, it enables tri-objective optimization of energy, throughput, and latency that has remained largely unexplored in current literature (Elgarhy et al., 2024), (Feng et al., 2025). Thirdly, it provides a decision-support framework that assists system designers in selecting the most suitable operating configuration depending on application requirements. Such as energy-constrained IoT sensing, high-throughput URLLC, or low-latency control loops (Elgarhy et al., 2024), (Qi et al., 2022).

This study demonstrates that combining surrogate modeling with evolutionary optimization provides an efficient and scalable mechanism for understanding and optimizing 6G IoT performance (Ananthanarayanan et al., 2025), (Krishnamoorthy et al., 2025). It will highlight promising directions for future AI-assisted wireless system design.

1.1 Objectives

This study aims to analyze the real 6G IoT beamforming dataset to understand the trade-off behavior among energy consumption, latency, and throughput, and to identify the empirical Pareto structure within these KPIs. A model is developed for a multi-output machine-learning surrogate to approximate the KPI mapping, and NSGA-II is integrated with the surrogate to efficiently perform tri-objective optimization. The objective is to generate extended Pareto-optimal solutions and visualize the 3D trade-off landscape and ultimately provide a decision-support framework that helps system designers select the most suitable beamforming configuration for energy-efficient, low-latency, or high-throughput 6G IoT applications.

2. Literature Review

In the race toward 6G, researchers are trying to solve three major challenges for IoT: how to make communication faster (high throughput), more energy-efficient, and with less delay (low latency). These goals often conflict, so recent studies have focused on balancing them, but most have done so partially or indirectly.

For example, ultra-massive MIMO systems have been tested at THz frequencies to boost throughput (Hoque & Huq, 2025) and hybrid beamforming has shown promise in reducing hardware complexity (Nassar et al., 2025). They have also shown that beam-domain modeling also simplifies signal processing by using sparse representations (Ihsan et al., 2022). However, these works have mainly focused on throughput and hardware feasibility. They have not offered a full picture of energy–latency–throughput trade-offs.

Some researchers have used computer vision to improve beamforming accuracy and speed (Ahn et al., 2023), which helps reduce latency. Others optimize energy efficiency in NB-IoT by tweaking resource unit configurations (Elgarhy et al., 2024), showing that energy use can vary by up to 80% depending on scheduling (Elgarhy et al., 2024). But again, these studies have shown energy and latency separately, not together with throughput.

The RIS-based beamforming has gained attention too. Passive RIS is great for low-power IoT, while active RIS boosts coverage (Dilli, 2022). Combining RIS with NOMA improves energy efficiency and user fairness (Feng et al., 2025), but these methods have not visualized or quantified the trade-offs between all three objectives.

AI and ML have brought new tools to the table. Deep learning models like CNNs and LSTMs improve spectral efficiency and reduce distortion (Ananthanarayanan et al., 2025), and quantum reinforcement learning speeds up decision-making while saving energy (Krishnamoorthy et al., 2025). Virtualized beamforming via software control also reduces power use and boosts performance (Alwakeel, 2025). Yet, most of these approaches are black-box optimizations. They have not shown users how energy, latency, and throughput interact.

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Some systems go beyond communication and include sensing and computation. ISCC frameworks use beamforming to support edge computing and object detection (Qi et al., 2022), and HAPS platforms offer wide-area coverage with better sensing accuracy than drones and satellites (Kanani et al., 2025). These are powerful ideas, but they still lack a clear decision-support model for balancing the three objectives.

3. Methods

In this paper, we used a dataset obtained from Kaggle. Our proposed methodology has been followed by a multistage data-driven optimization pipeline designed for tri-objective performance improvement in 6G IoT beamforming. The process has begun with loading the real 6G IoT beamforming dataset and performing data preprocessing to ensure consistency across numerical and categorical features. We have had standard scaling applied to continuous variables, and categorical parameters have been converted into machine-readable formats using one-hot encoding. After preparing the dataset, the three target KPIs, namely energy, latency, and throughput, were separated, enabling an initial empirical analysis of their joint behavior.

To understand the inherent trade-offs among the KPIs, an empirical Pareto detection step has been conducted using non-dominated sorting. This step reveals the natural conflicts among the objectives and provides a baseline Pareto boundary that has been directly extracted from the dataset. However, relying solely on empirical data limits the search space to existing samples; therefore, a predictive surrogate model has been developed to explore unseen configurations. A multi-output regression model (Random Forest) was trained to approximate the nonlinear mapping between the input beamforming parameters and the three KPIs.

Next, we combined the surrogate model with the NSGA-II algorithm to optimize the three objectives simultaneously. In this step NSGA-II generates several possible beamforming configurations and improves them step by step. It uses crossover, mutation and selection to improve, while non-dominated sorting and crowding distance metrics are used. Algorithms simultaneously reduce energy and latency, and increase data rate (Throughput). Surrogate-driven NSGA-II can explore a larger design space beyond the original dataset and produces a dense, smooth Pareto frontier showing the optimal trade-off.

The optimized solutions are then analyzed with various visualization tools. Two-dimensional graphs show pairwise trade-offs of Energy, Latency, and Throughput, while three-dimensional plots reveal the full three-objective picture. These visualizations show how changing one KPI affects others and help system designers choose the right operating point. Such as low power consumption configurations, low latency settings, or balanced “knee-region” solutions. The whole process has led to the decision-support framework proposed in this study (Figure 1 and Figure 2).

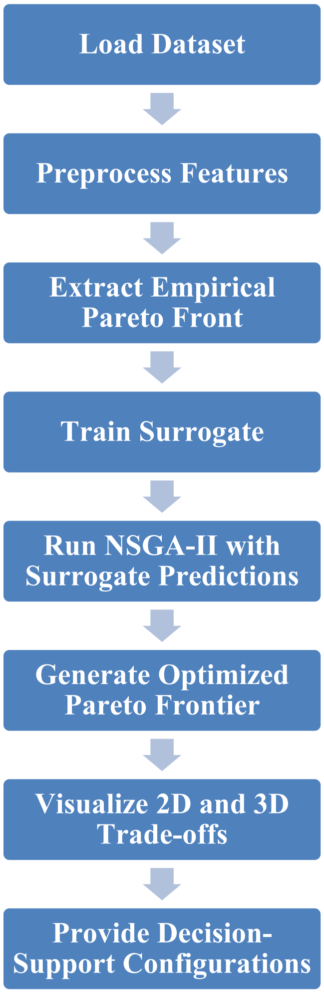

Figure 1. Workflow for Multi-Objective Optimization Process

4. Results and Discussion

A. 3D Pareto Frontier of Energy, Latency, and Throughput Trade offs

A 3D analysis is shown in Figure 2 where three important performance metrics are considered together: energy consumption (kWh/Gb), data rate or throughput (Mbps), and delay or latency (s). This visualization includes three types of datasets

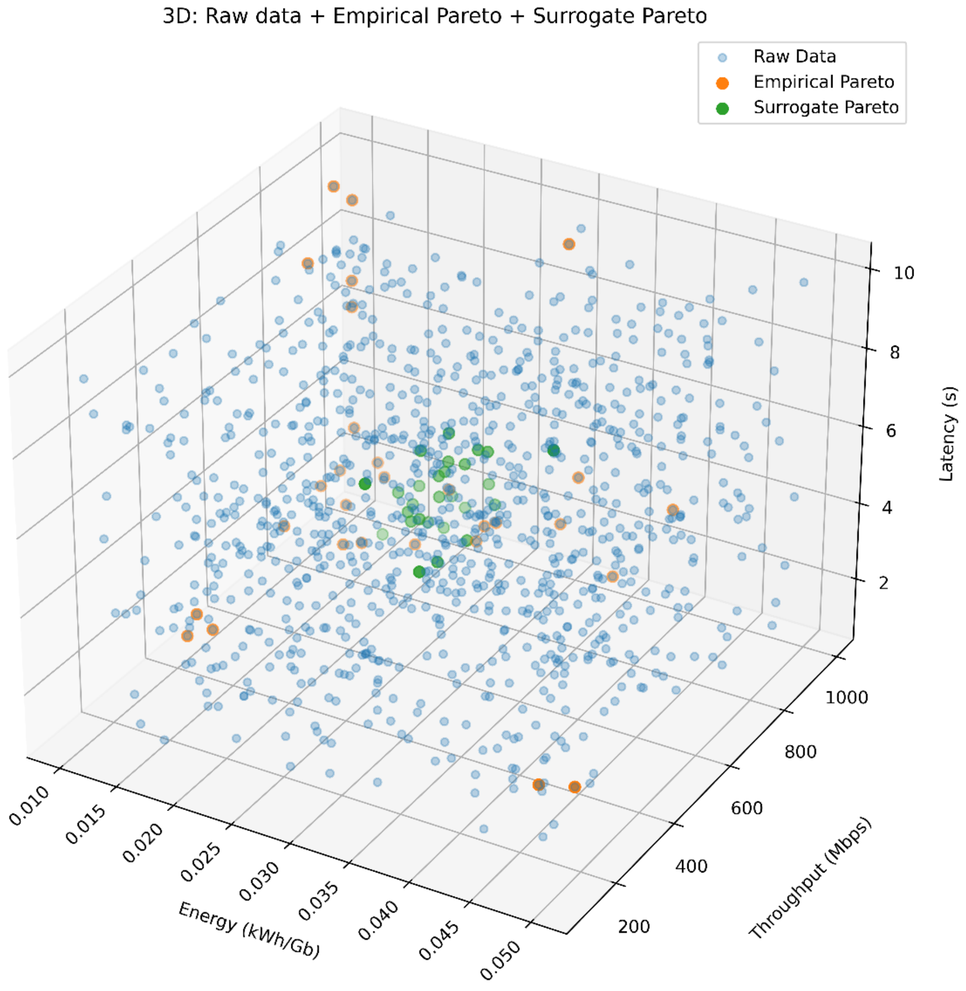

Figure 2. 3D Pareto Frontier of Energy, Latency, and Throughput Trade-offs

:

- Raw Data (light blue): This shows the original measured configurations, which are spread over all three axes.These reflect the baseline performance of the system without any optimization.
- Empirical Pareto (orange): They have shown configurations taken directly from Raw Data that lie on the Pareto frontier.These are providing the best balance between power, throughput and latency.
- Surrogate Pareto (green): Created by running NSGA-II optimization on the surrogate model. They form a smooth and dense Pareto frontier and show high-performance regions that are not directly visible in the raw data.

The plot shows that Surrogate Pareto points are generally clustered in regions of low energy consumption and low latency, while maintaining competitive throughput. This has proven that the surrogate-driven optimization framework is effective.

This comparative visualization shows that surrogate modeling can significantly increase design space exploration, especially when multiple goals are to be considered simultaneously. such as energy efficiency, real-time responsiveness, and high data throughput. The consistency between the Empirical and Surrogate Pareto points further confirms that the surrogate model is able to accurately approximate the true performance frontier.

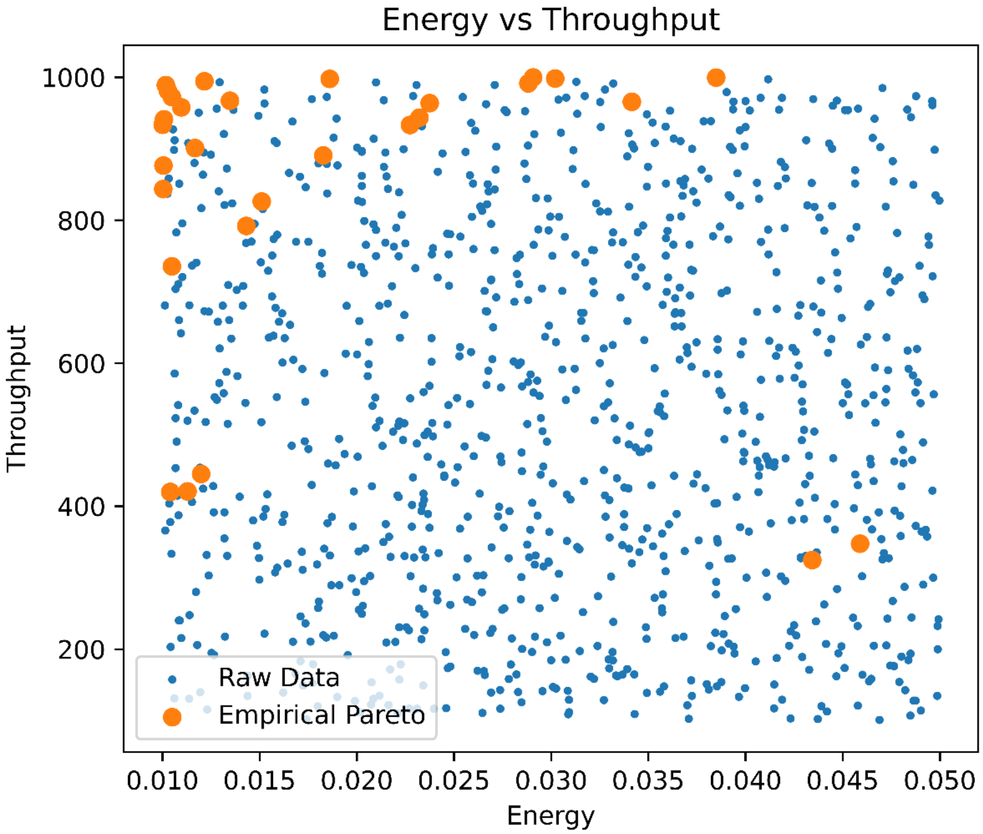

Figure 3. 2D Pareto Analysis of Energy vs Throughput

B. 2D Pareto Analysis of Energy vs Throughput

Figure 3 presents a two-dimensional trade-off analysis between energy consumption (kWh/Gb) and throughput (Mbps), highlighting the performance distribution across the measured configurations. The visualization includes two distinct datasets. Raw data (light blue) and empirical Pareto (orange).

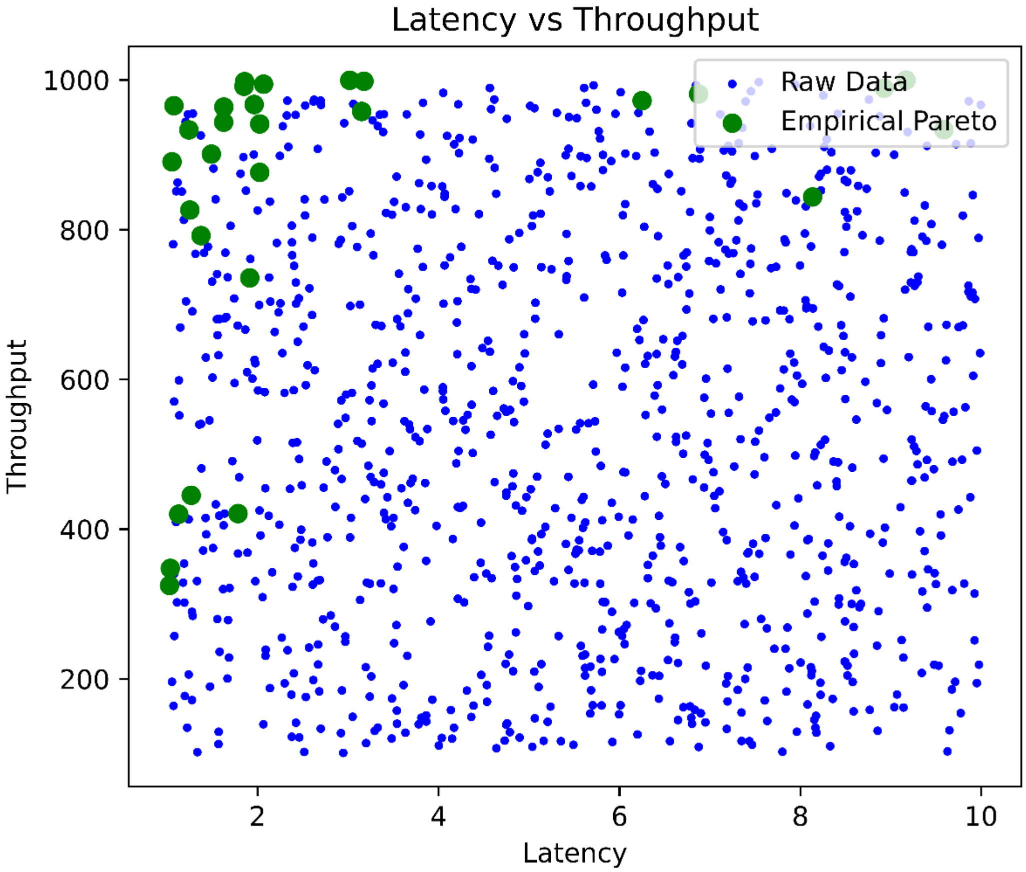

Figure 4. 2D Pareto Analysis of Latency vs Throughput

C. 2D Pareto Analysis of Latency vs Throughput

Figure 4 presents a two-dimensional trade-off analysis between latency (s) and throughput (Mbps), highlighting the performance distribution across the measured configurations. The visualization includes two distinct datasets. Raw data (light blue) and empirical Pareto (green).

5. Conclusion

In this study, we have shown a comprehensive multi-objective optimization framework for 6G IoT beamforming using a real dataset. We have highlighted the inherent conflict among energy, latency, and throughput KPIs and demonstrated that no single configuration can optimize all objectives simultaneously. We have had a surrogate-based NSGA-II algorithm successfully generate a dense and smooth Pareto frontier, enabling the selection of the feasible operating regions for different IoT use cases.

Our results ensure that machine learning-assisted surrogate modeling is an effective approach for handling complex KPI relationships in next-generation wireless systems. Moreover, the generated 3D trade-off landscape provides practical decision support for system designers, helping them to select balanced configurations depending on energy constraints, latency sensitivity, or throughput demand.

In the future, we will focus on integrating additional beamforming parameters, expanding the dataset, and deploying reinforcement learning or online optimization schemes to enable a real-time adaptive configuration.

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