

# Ablation Study on Feature Engineering Strategies for Fairness-Driven LEO Direct-to-Cell

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**Abstract**—This work presents an ablation study on feature engineering strategies for fairness-aware LEO direct-to-cell (DTC) resource allocation. We systematically evaluate raw channel processing, engineered features, and compressed representations (classical 4D and quantum 2D bottlenecks). Surprisingly, raw channels achieve 45% higher fairness (FDAU = 1.076) than compressed methods (0.710–0.741), revealing a fundamental fairness-compression trade-off where aggressive dimensionality reduction destroys user correlation information critical for balanced rate allocation.

**Index Terms**—direct-to-cell, fairness, quantum machine learning, resource allocation, RSMA

## I. INTRODUCTION

LEO satellite DTC networks enable ubiquitous smartphone connectivity without terrestrial infrastructure [1]. However, dense mega-constellations introduce severe inter-satellite interference, while rapid user mobility and heterogeneous traffic demands complicate fair resource allocation. Traditional optimization methods exhibit prohibitive computational complexity unsuitable for real-time satellite operations [2].

RSMA offers robust interference management through common-private stream splitting [3], while spatial-temporal (ST) extensions exploit Doppler diversity in mobile scenarios [2]. However, existing fairness metrics like capacity-demand gap penalize oversupply and under-supply symmetrically, obscuring meaningful efficiency-fairness tradeoffs [4].

Quantum machine learning demonstrates potential for wireless optimization through enhanced representational capacity [5]. Recent variational quantum circuits achieve strong performance in high-dimensional control tasks [6], yet lack integration with fairness-aware resource allocation for satellite networks.

This work presents an ablation study on ST-RSMA for LEO DTC networks with contributions: (1) A FDAU metric with asymmetric logarithmic structure, (2) Systematic evaluation revealing raw channels outperform compressed methods by 45%, and (3) Analysis identifying fairness-compression trade-offs where dimensionality reduction degrades user correlation preservation.

## II. SYSTEM MODEL AND Q-STPR FRAMEWORK

### A. ST-RSMA with FDAU Metric

A LEO satellite at altitude  $h = 600$  km with  $N_t = 4$  antennas serves  $K = 4$  DTC ground users (each with  $M = 2$  antennas) over  $T = 2$  time slots. The ST channel to user  $k$

at slot  $t$  incorporates 3GPP NTN path loss  $\beta_k$  and Doppler shifts:

$$\mathbf{H}_k(t) = \sqrt{\beta_k} \mathbf{G}_k(t) \odot \exp(j2\pi f_{D,k} t \Delta t), \quad (1)$$

where  $f_{D,k} = v_k f_c / c$  with user velocity  $v_k \sim \mathcal{U}[0, 120]$  km/h at carrier frequency  $f_c = 20$  GHz.

RSMA transmission combines common stream  $s_c(t)$  and private streams  $\{s_k(t)\}$ :

$$\mathbf{x}(t) = \mathbf{f}_c(t) s_c(t) + \sum_{k=1}^K \mathbf{f}_p^{(k)}(t) s_k(t), \quad (2)$$

subject to power constraint  $\frac{1}{T} \sum_{t=1}^T (\|\mathbf{f}_c(t)\|^2 + \sum_k \|\mathbf{f}_p^{(k)}(t)\|^2) \leq P_{\max}$  and minimum rate  $R_k \geq R_{\min} = 1.0$  bps/Hz  $\forall k$ . The achievable rate per user:

$$R_k = \frac{1}{T} \sum_{t=1}^T \left( \frac{R_c(t)}{K} + \log_2(1 + \gamma_{p,k}(t)) \right). \quad (3)$$

For heterogeneous demands  $D_k \sim \mathcal{U}[2, 6]$  bps/Hz (challenging scenario), FDAU is proposed:

$$\text{FDAU} = \frac{1}{K} \sum_{k=1}^K \log \left( 1 + \frac{R_k}{D_k} \right). \quad (4)$$

This logarithmic structure provides diminishing returns for oversupply while heavily penalizing under-supply, enabling efficient surplus allocation unlike symmetric CD-gap metrics.

### B. Q-STPR Architecture

Fig. 1 illustrates Q-STPR’s three-stage pipeline. **Stage 1** extracts  $D = 38$  dimensional features comprising spatial characteristics (channel strength, correlations, phase relationships), temporal dynamics (magnitude variation, phase change), and Doppler statistics (shifts, velocity proxies).

**Stage 2** employs a 2-qubit VQC for ultra-compact feature compression. After Hadamard initialization for superposition, feature encoding via  $\mathbf{x} = \tanh(\mathbf{W}_{\text{enc}} \phi)$  followed by  $R_y$  rotations creates input-dependent quantum states. Linear Controlled-Z gates induce entanglement between qubits. A variational layer with parametrized  $R_y$  and  $R_z$  rotations yields 4 trainable quantum parameters (2 qubits  $\times$  2 rotation types). Pauli-Z measurements extract 2-dimensional quantum features, achieving 19:1 compression ratio (38D  $\rightarrow$  2D), expanded to 32-dimensional policy  $\pi = \tanh(\mathbf{W}_{\text{dec}} \mathbf{q} + \mathbf{b}_{\text{dec}})$ .

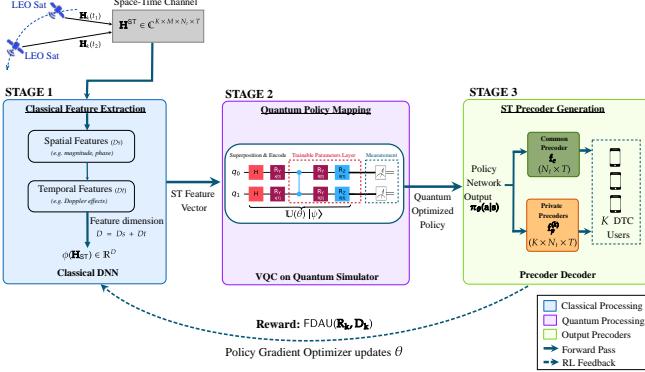


Figure 1: Q-STPR framework. **Top:** LEO satellite serving  $K = 4$  DTC users. **Bottom:** Three-stage architecture: **(1)** ST feature extraction (38D), **(2)** 2-qubit VQC (4 parameters, 19:1 compression), **(3)** ST precoder generation.

**Stage 3** maps the policy to space-time precoders  $\{\mathbf{f}_c(t), \mathbf{f}_p^{(k)}(t)\}$  via time-specific decoders with power normalization. The model maximizes expected FDAU subject to power and minimum rate constraints through penalty-based policy gradient optimization:

$$\mathcal{L}(\theta) = -\mathbb{E}_{\mathbf{H}, \mathbf{D}} [\text{FDAU} - \lambda_{\text{pow}} \mathcal{P}_{\text{pow}} - \lambda_{\min} \mathcal{P}_{\min}], \quad (5)$$

where  $\mathcal{P}_{\text{pow}} = \max(0, P_{\text{avg}} - P_{\text{max}})$  and  $\mathcal{P}_{\min} = \max(0, R_{\min} - \min_k R_k)$  are constraint violation penalties.

### III. EXPERIMENTAL RESULTS

LEO satellite parameters follow 3GPP NTN standards with  $P_{\text{max}} = 30$  dBm,  $B_{\text{bw}} = 400$  MHz, noise power  $\sigma^2 = -90$  dBm, yielding SNR of 10–20 dB. User velocities span 0–120 km/h with heterogeneous demands  $D_k \sim \mathcal{U}[2, 6]$  bps/Hz. Performance evaluation uses 100 test samples.

Fig. 2 shows training convergence across four methods: C-STPR (raw channels), CF-STPR (engineered features), CFB-STPR (classical 4D bottleneck), and Q-STPR (quantum 2D bottleneck). All methods converge within 10 episodes with Q-STPR maintaining lowest variance.

Table I reveals raw channel processing (C-STPR) achieves highest FDAU (1.076), outperforming compressed methods by 45%. Feature engineering degrades fairness by  $-31.1\%$  (C→CF) through information aggregation. Further compression provides no benefit: classical bottleneck (CF→CFB) shows  $-1.6\%$  loss, while quantum compression (CFB→Q) yields additional  $-2.6\%$  degradation. This demonstrates that fairness requires preserving user-specific correlations, which compression destroys. C-STPR also achieves highest sum rate (21.14 bps/Hz), suggesting raw channels enable both capacity and fairness.

### IV. CONCLUSION

This ablation study reveals a fundamental fairness-compression trade-off in LEO DTC resource allocation: raw channels achieve 45% higher fairness than compressed methods by preserving user-specific correlations. Feature engineering and compression (classical or quantum) degrade fairness

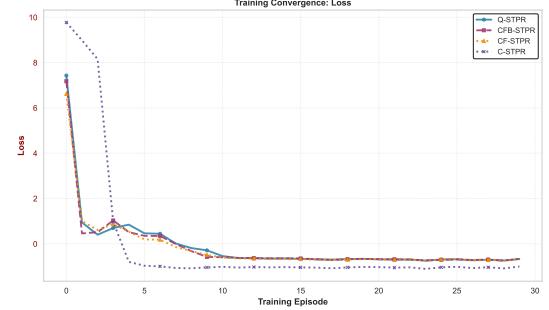


Figure 2: Training convergence: all learning methods achieve similar convergence speed, with Q-STPR maintaining lowest variance.

Table I: Ablation Study: Feature Engineering Impact

Method	Bottleneck	Ratio	FDAU	Sum Rate (bps/Hz)
C-STPR (Raw)	None	1.0	<b>1.076</b>	<b>21.14</b>
CF-STPR (Feat)	None	1.7	0.741	6.97
CFB-STPR (Class)	4D	9.5	0.729	6.79
Q-STPR (Quant)	2D	19.0	0.710	6.85
$\Delta(C \rightarrow CF): -31.1\% \text{ FDAU}; \Delta(CF \rightarrow CFB): -1.6\%; \Delta(CFB \rightarrow Q): -2.6\%$				

BN: bottleneck dimension; Ratio: compression ratio (input/bottleneck)

through information loss. Future work includes hybrid architectures and higher-qubit quantum circuits (4–8 qubits) for improved compression-fairness balance.

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### REFERENCES

- [1] X. Chen and Z. Luo, "Asynchronous interference mitigation for leo multi-satellite cooperative systems," *IEEE Transactions on Wireless Communications*, 2024, published online 2024.
- [2] J. Seong, B. Lee, A. Kaushik, and W. Shin, "Space-time rate-splitting multiple access for multibeam leo satellite networks," *IEEE Transactions on Vehicular Technology*, Oct. 2025.
- [3] J. Seong, J. Park, J. Lee, J.-B. Kim, W. Shin, and H. V. Poor, "Rate-matching framework for rsma-enabled multibeam leo satellite communications," *IEEE Transactions on Signal Processing*, Feb. 2025.
- [4] L. Lei, A. Wang, E. Lagunas, X. Hu, Z. Zhang, Z. Wei, and S. Chatzinas, "Spatial-temporal resource optimization for uneven-traffic leo satellite systems: Beam pattern selection and user scheduling," *IEEE Journal on Selected Areas in Communications*, vol. 42, no. 5, pp. 1279–1291, Apr. 2024.
- [5] J. Zhang, G. Zheng, T. Koike-Akino, K.-K. Wong, and F. Burton, "Hybrid quantum-classical neural networks for downlink beamforming optimization," *IEEE Transactions on Wireless Communications*, Aug. 2024.
- [6] G. Kaddoum *et al.*, "Quantum adaptive learning for coverage optimization in leo satellite network," in *ICC 2025-IEEE International Conference on Communications*. IEEE, Jun. 2025, pp. 2382–2387.