Quantum Computing in the RAN with Qu4Fec: Closing Gaps Towards Quantum-based FEC Processors

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Motivation and Research Goal

- Wireless baseband processing is the most power-intensive tasks in 5G and future 6G networks.
  - Baseband processors can consume up to **350 kW** depending on MIMO and antenna configurations. [1]

[1] Kasi et al., IEEE Trans. Quantum Engineering, 2023

[2] Villalonga-Correa et al., Quantum Sci. Technol., 2023

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- Quantum computing is emerging as a promising solution for complex, compute-heavy problems.
  - Potential to reduce baseband-related power consumption to **25–30 kW**. [2]

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Research Goal:
Explore the feasibility and hardware constraints of quantum-based **FEC decoding** in future wireless systems.

[1] Kasi et al., IEEE Trans. Quantum Engineering, 2023
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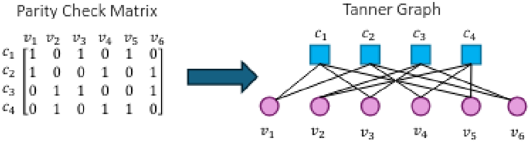
- Low-Density Parity-Check (LDPC) codes are FEC codes defined by a sparse $m \times n$ parity-check matrix $\mathbf{H}$.
- A valid codeword satisfies the constraint: $\mathbf{H} \cdot \mathbf{c}^T = \mathbf{0}$
- LDPC codes can also be visualized using a **Tanner graph**



LDPC Decoding

Maximum-Likelihood (ML) Decoding

- Let $\hat{\mathbf{y}}$ be the received signal after transmitting codeword $\mathbf{y}$ over a noisy channel.
- The ML decoder finds the most probable transmitted codeword:

$$\hat{\mathbf{x}} = \arg\max_{\mathbf{x}\in\mathcal{C}} P(\mathbf{x} \mid \hat{\mathbf{y}})$$

Belief Propagation (BP) Decoding

- BP is an iterative algorithm that approximates ML decoding.

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- A quantum annealer (QA) is a specialized quantum computer designed to solve **Quadratic Unconstrained Binary Optimization (QUBO)** problems.

$$E(q) = \sum_i h_i q_i + \sum_{i<j} J_{ij} q_i q_j$$

- $q_i \in \{0, 1\}$ are binary decision variables.
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Primer to Quantum Annealers

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Solving a Problem on a Quantum Annealer:

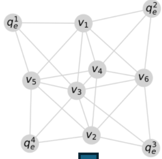
1. Formulate the problem as a QUBO.
2. Map logical variables to chains of physical qubits (**embedding**).
3. Program qubits and couplers with h_i and J_{ij}.
4. Run the annealing process to minimize $E(q)$.
5. Retrieve and analyze the solutions.

- Every QUBO defines a **source graph** that needs to be mapped to the **target graph**, defined by the physical qubit layout of the Quantum hardware (e.g., D-Wave)

a) Parity Check Matrix

$$\begin{array}{c} \\ c_1 \\ c_2 \\ c_3 \\ c_4 \end{array} \begin{array}{c} \begin{array}{cccccc} v_1 & v_2 & v_3 & v_4 & v_5 & v_6 \end{array} \\ \begin{bmatrix} 1 & 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

b) QUBO (source graph)

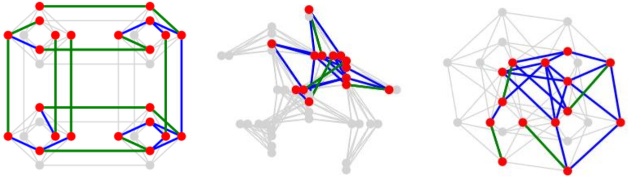


c) QPU (target graph)

Chimera

Pegasus

Zephyr



Qu4Fec – Proposal

- We propose **Qu4Fec** — a problem formulation for quantum-based LDPC decoding.
- We rely on well-established code design techniques from the literature (e.g., Gallager codes)
- We provide a new problem formulation *directly derived from the fundamental maximum-likelihood (ML) decoding problem for LDPC codes*.
  - This ensures that the solution estimated by the QA is formally guaranteed to be the ML solution.

Qu4Fec – LDPC Decoding QUBO

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  1. **ML-derived objective:** Starting from the fundamental ML decoding formulation, we derive the correlation term (for BPSK modulation) as:

$$Q_C = \sum_{k=1}^{n} -y_k(1 - 2q_k)$$

where $q_k \in \{0, 1\}$ represents the k-th bit of the estimated codeword.

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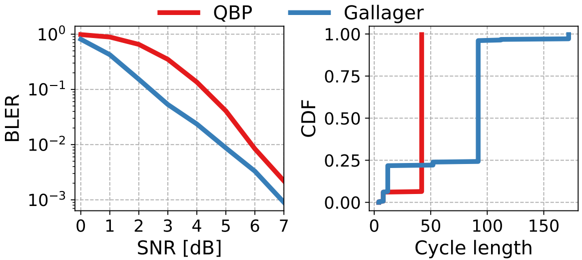
- We formally prove that this formulation **guarantees the QUBO's minimum-energy solution coincides with the ML solution**.

QBP – Limitations

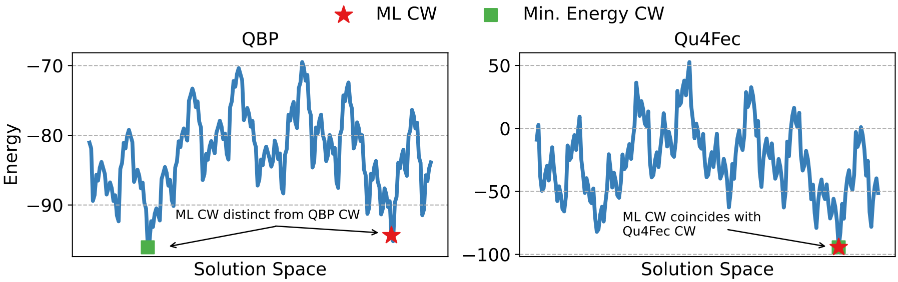
- **QBP** [3] was the first to formulate LDPC decoding on a QA.
- QBP **tailors the LDPC code** to the qubit topology of the quantum annealer.
  - This often results in Tanner graphs with **short cycles**, weakening the LDPC code's performance.
- In contrast, Qu4Fec uses Gallager codes.



[3] Kasi et al., "Towards Quantum Belief Propagation for LDPC Decoding in Wireless Networks," MobiCom 2020

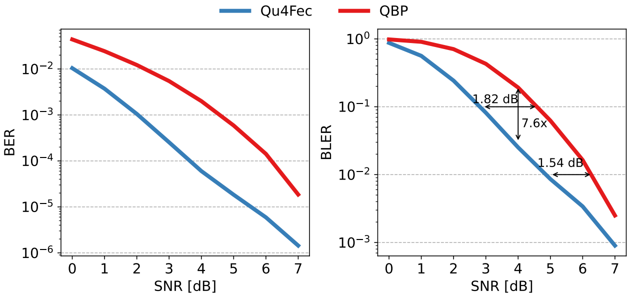
QBP – Limitations (cont'd)

- The QBP formulation **does not originate** from the ML objective.
- QBP QUBO's minimum energy solution often **does not match** the ML-optimal codeword.
- QBP pretunes the hyperparameter a according to SNR.



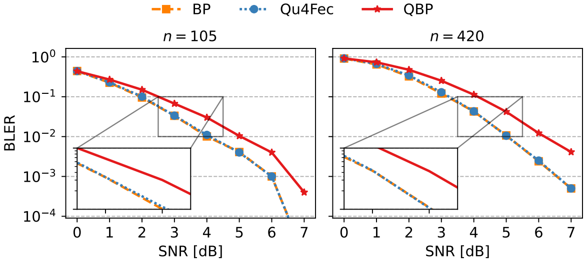
Qu4Fec – Evaluation

- We evaluated the impact of code design and QUBO formulation on decoding performance using **Simulated Annealing (SA)**
- Results show significant improvements in **BLER** across a wide SNR range.



Qu4Fec – Evaluation (cont'd)

- To isolate the effect of QUBO formulation, all methods used the same Gallager-designed LDPC code.



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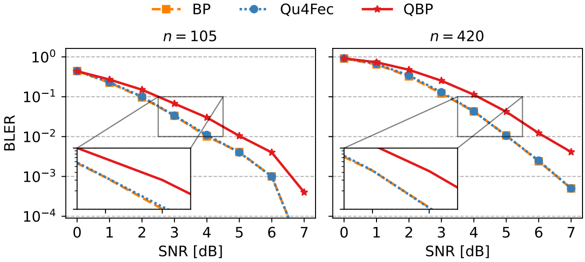
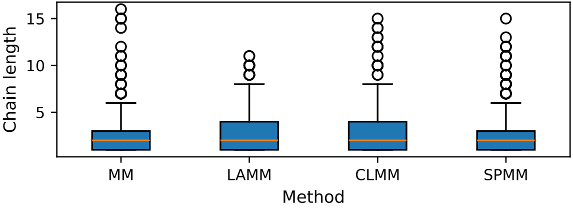


- Testing both Qu4Fec and QBP on actual QA resulted in degraded performance, attributed to **non-deal embeddings** and **scaling and quantization impact**.

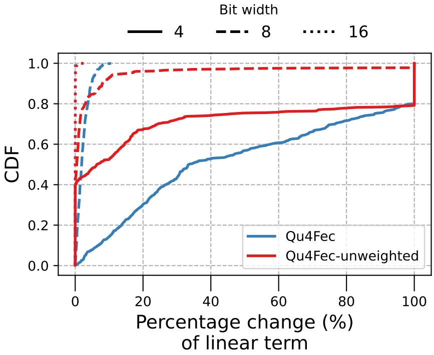
Effect of Non-Ideal Embeddings

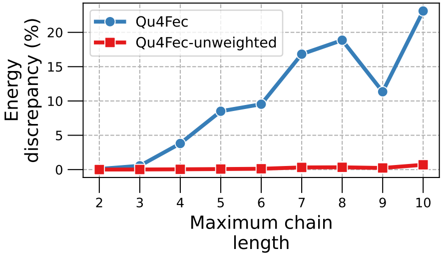
- The noise in QAs result in perturbed linear and quadratic terms $h + \delta h, \quad J + \delta J$
- The sparse connectivity of the qubit graph forces the embedding to form longer chains of physical qubits.
- We experimented with multiple embedding heuristics beyond the default Minorminer (MM): **LAMM**, **CLMM**, and **SPMM**.



Effect of Scaling and Quantization

- Before programming the QA
  1. All terms are **scaled**: $h \in [-4, 4], \quad J \in [-1, 1]$,
  2. and **quantized** with limited precision (e.g. 4, 8, 16-bit resolution)
- This discretization adds further distortion to the energy landscape and may alter the minimum-energy solution.





Conclusion

- Introduced **Qu4Fec** — a new QUBO formulation for LDPC decoding on quantum annealers — demonstrating superior BLER performance compared to QBP.
- Conducted extensive evaluation on quantum annealers, revealing key hardware limitations — including non-ideal embeddings and quantization effects.
- **Advise** the full paper for more details and results (e.g. extensions of QA to address the LDPC codes) !
- **Future direction**: explore the design of **quantum-native error correction codes** that match the connectivity and noise characteristics of current QAs

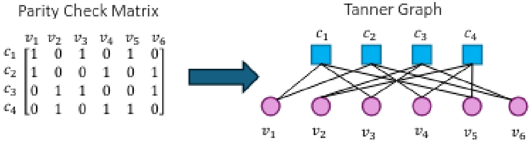
Thank You!

Supported by:

Appendix

Primer to LDPC Codes

- Low-Density Parity-Check (LDPC) codes are FEC codes defined by a sparse $m \times n$ parity-check matrix $\mathbf{H}$.
- Each row in $\mathbf{H}$ defines a parity-check constraint; each column corresponds to a bit in the codeword $\mathbf{c} \in \{0, 1\}^n$.
- A valid codeword satisfies the constraint: $\mathbf{H} \cdot \mathbf{c}^T = \mathbf{0}$
- LDPC codes can also be visualized using a **Tanner graph** — a bipartite graph with:
  - Variable nodes (codeword bits)
  - Check nodes (parity constraints)
  - Edges corresponding to 1s in $\mathbf{H}$



$$
\begin{array}{c|cccccc}
 & v_1 & v_2 & v_3 & v_4 & v_5 & v_6 \\
\hline
c_1 & 1 & 0 & 1 & 0 & 1 & 0 \\
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- The ML decoder finds the most probable transmitted codeword:

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- ML decoding is optimal but computationally intractable for large codes.

Belief Propagation (BP) Decoding

- BP is an efficient iterative algorithm that approximates ML decoding.
- It operates on the Tanner graph using message passing between variable and check nodes.

QBP: LDPC Decoding as a QUBO

- **Quantum Belief Propagation (QBP)** [4] was the first to formulate LDPC decoding on a quantum annealer (QA).
- For a codeword of n bits, QBP outputs a binary vector: $q_1, q_2, \ldots, q_n$
- The QUBO formulation is:

$$Q = a \cdot Q_{\text{LDPC}} + Q_C$$

  where:
  - Q_{LDPC} encodes the hard parity-check constraints.
  - Q_C captures the correlation with the received noisy vector $\hat{\mathbf{y}}$.
  - a is a weighting factor (dependent on SNR), requiring hyperparameter tuning.

[4] Kasi et al., "Towards Quantum Belief Propagation for LDPC Decoding in Wireless Networks," MobiCom 2020