HW3: Quantum Annealers - Experimental Report

Quantum Computer Architecture and Systems

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1 Embedding Search Setup

Tested embedding on **3 D-Wave QPUs**: Advantage_system6.4, Advantage_system4.1, and Advantage2_system1.8, evaluating 5 graph families (SK, 3-regular, ER, BA-1, BA-2). All solvers successfully embedded graphs at **N=120** for all families. Advantage_system6.4 was selected for subsequent experiments.

2 Simulated Annealing Baseline (Mean BSS)

We generated 75 problem instances (5 graph types $\times$ 3 coefficient distributions $\times$ 5 instances) and solved with SA using 1000 reads per instance. BSS = $E_{\min} \times f_{\min}$ (more negative = better):

Graph Type	Gaussian	Random (±1)	Uniform
SK	**-235,932.84**	-117,183.20	-104,853.39
ER	-136,963.91	-112,012.00	-81,446.66
BA-2	-17,516.37	-19,175.20	-26,129.33
BA-1	-36,367.73	-151.80	-11,174.19
3-reg	-4,843.68	-179.20	-10,467.00

Table 1: SA Mean BSS by Graph Type and Coefficient Distribution

Dense graphs (SK, ER) achieve significantly more negative BSS, with Gaussian coefficients generally producing the best results.

3 Quantum Annealing Results (Mean BSS)

Using the same 75 instances on Advantage_system6.4:

Graph Type	Gaussian	Random (±1)	Uniform
SK	-938.50	-930.80	-544.24
ER	-641.11	-648.00	-387.57
BA-2	-187.90	**-8,647.20**	-477.71
3-reg	-169.70	-179.20	-460.80
BA-1	-140.41	-151.80	-87.01

Table 2: QA Mean BSS by Graph Type and Coefficient Distribution

QA BSS values are dramatically less negative than SA, indicating significantly worse raw performance.

4 SA vs QA Comparison

We computed the relative performance metric $R = \text{BSS}_{\text{QA}}/\text{BSS}_{\text{SA}}$ where $R > 1$ means QA better, $R < 1$ means SA better:

Graph Type	Gaussian	Random (±1)	Uniform
SK	**0.007**	0.015	**0.006**
ER	**0.008**	**0.007**	**0.007**
BA-2	0.036	0.311	0.037
3-reg	0.049	**1.000**	0.040
BA-1	0.013	**1.000**	0.009

Table 3: Mean Relative Performance R (SA vs QA)

Overall: SA wins 65/75 instances (86.7%), QA wins 0/75 instances (0%), with 10 similar.
Key Findings:

- **Dense graphs (SK, ER)**: SA dominates strongly ($R < 0.01$), winning 100% of instances
- **Sparse graphs (3-reg, BA-1)**: SA still wins but with smaller margin ($R \approx 0.3 - 0.4$)
- **Continuous coefficients (Gaussian, Uniform)**: SA overwhelmingly superior ($R \approx 0.02$)
- **Discrete coefficients (Random ±1)**: SA wins moderately ($R = 0.47$), 40% similar performance
- **No graph family favors QA** in raw performance

5 Postprocessing with Steepest Descent

We applied steepest descent postprocessing to all SA and QA samples:

Sampler	Mean Improvement	Instances Improved
SA	+2.76%	10/75 (13.3%)
QA	**+2,571.85%**	62/75 (82.7%)

Table 4: Postprocessing Impact on SA and QA

QA benefits 932× more than SA from postprocessing.

By Graph Family: QA improvements range from +85% (ER) to +11,171% (BA-1), while SA improvements are 0-8.57%. Sparse graphs (BA-1, BA-2) benefit most from QA postprocessing.

By Coefficient Distribution: Continuous coefficients (Gaussian +4,120%, Uniform +3,558%) show dramatically larger QA improvements than discrete coefficients (Random ±1: +38%).

6 Why SA and QA Respond Differently

The 932× difference reveals fundamental algorithmic distinctions:

SA's minimal improvement (+2.76%) indicates solutions are already near local optima. Classical simulated annealing performs continuous local search during cooling, ensuring convergence to stationary points.

QA's massive improvement (+2,572%) reveals three factors:

1. **Distance from local optima**: QA uses quantum tunneling to traverse energy barriers without necessarily descending to minima. Short annealing times (20-100μs) prevent full classical relaxation.

2. **Hardware imperfections**: Chain breaking (from embedding 120 logical qubits onto physical chains), ICE (integrated control errors), and calibration issues introduce systematic errors that classical postprocessing corrects.

3. **Coefficient distribution mismatch**: QA struggles with continuous coefficients ($R = 0.02$) but performs relatively better with discrete values ($R = 0.47$), suggesting hardware optimization for discrete problems. Postprocessing is essential for continuous landscapes.

The evidence strongly supports that QA identifies promising regions via quantum effects but requires classical refinement to reach local optima, while SA already completes this process internally.