Calibrating Simulations of Quantum Annealers for Predictive Models

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1 INTRODUCTION

Despite the interest in using quantum annealing (QA) to provide a speedup over classical methods for optimization problems, evaluations have rarely achieved this. In order to improve the performance of the annealers, some researchers focus on modifying the annealing schedule. One modification that can significantly improve performance is a mid-anneal pause, which is parameterized by a pause location that determines whether a pause is effective, and a pause duration that influences the performance improvement. We focus on the pause location, for which the optimal value is problem dependent and typically found via a costly grid search. Our recent work demonstrated that the combination of simulations and deep learning models can quickly predict a pause location that improves performance while avoiding the costs associated with a grid search [2]. However, our results also showed that the simulator needs refinement in order to capture the full benefit of a pause.

2 METHODS

Our previous work simulates QA with spin-vector Monte Carlo with transverse-field-dependent updates (SVMC TF), a model that was shown to reproduce the effects of a mid-anneal pause [1]. In this work, we compare the effects of pausing in QA and SVMC TF. We focus on the number of sweeps, or iterations, of SVMC TF, which can be thought of as an analogue for time in QA. We anneal and simulate anneals with pauses between 0.3 and 0.7 at intervals of 0.01. For QA, we use an anneal time of 1µs and a pause duration of 1µs. For SVMC TF, we use 10,000 annealing sweeps, and vary the number of pause sweeps from 1,000 to 15,000. The problems used in our evaluation contain 50 variables and we use 10 random instances per problem type, selected from the Sherrington Kirkpatrick model (SK) and the not-all-equal 3-satisfiability problem with a clause-to-variable ratio of 1 (NAE3SAT1) or 2 (NAE3SAT2).

3 RESULTS

Figure 1 shows the result of our evaluation. For QA, we show that each problem type has its own optimal pause location, and there is no pause location that will significantly reduce energy for all problem types. When comparing the results from SVMC TF for SK and NAE3SAT2, the figure shows that the pause location that decreases energy the most is earlier than the same location in QA. However, as we increase the number of sweeps from 1,000 to 15,000, the optimal pause locations in SVMC TF become closer to the optimal pause locations in QA. On the other hand, we see the opposite effect with NAE3SAT1; as the number of sweeps increases from 1,000 to 15,000, the simulated optimal pause location moves further away from the QA optimal pause location.

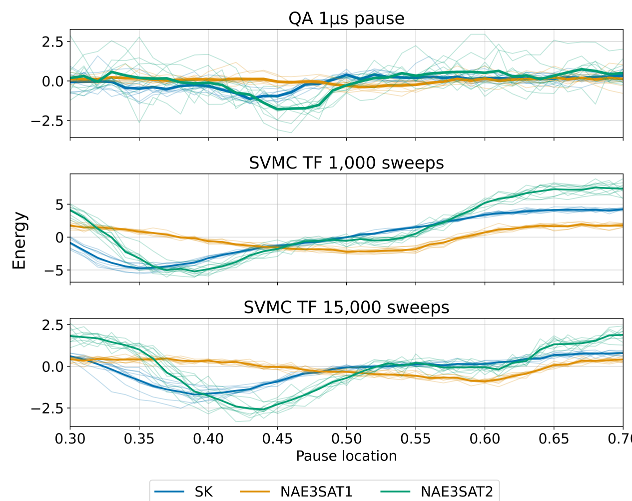

Figure 1: Average energy change due to a mid-anneal pause.

4 CONCLUSIONS

Our results show that there is no single value for sweeps in SVMC TF that results in accurate simulations for all types of problems. One method to find the optimal value for each problem type is to first profile the problem on the annealer, and then optimize the number of sweeps. However, this approach needs to be repeated for each new problem type, which would be costly and impractical. Our future interest is in modifying the simulation to reduce the difference in variation of optimal pause locations between QA and SVMC TF so that calibration can be performed at the annealer level rather than at the problem type level.

REFERENCES

[1] Tameem Albash and Jeffrey Marshall. 2021. Comparing Relaxation Mechanisms in Quantum and Classical Transverse-Field Annealing. *Phys. Rev. Appl.* 15 (Jan 2021), 014029. Issue 1.

[2] Michael Zielewski, Keichi Takahashi, Yoichi Shimomura, and Hiroyuki Takizawa. 2023. Efficient Pause Location Prediction Using Quantum Annealing Simulations and Machine Learning. *IEEE Access* 11 (2023), 104285–104294.