

Multi Basis Mixer QAOA Enhanced Memetic Tabu Search

I. Introduction

Current quantum-enhanced memetic tabu search for the low-autocorrelation binary sequences problem achieves $O(1.24^N)$ scaling using digitized counterdiabatic quantum optimization (DCQO) for population initialization. However, DCQO's single-basis evolution may leave certain structures in the energy landscape underutilized. As problem size increases MTS (Memetic Tabu Search) has exponential scaling and long time-to-solution behavior. MB-QAOA applies QAOA-style parametric rotations across multiple computational bases (X, Y, Z) to potentially access broader regions of the energy landscape and generate more diverse, high-quality initial populations. This population will then be inputted into the MTS algorithm which could improve runtime.

II. Specifications (Implementation & Verification)

We aim to implement MB-QAOA for LABS instances $N = 27-40$. A guess will be designed by ansatz incorporating two-body and four-body LABS interactions. Verification will be done by validating correctness against known optimal energies ($N \leq 30$) and comparing sample quality metrics to the given DCQO baseline.

III. Improvement Objectives

DCQO relies on operations in the Z-axis and corrective counterdiabatic measures using Y-rotations. This leaves possible routes of exploration using both X and Z bases available. This system is able to break down the large scale Hamiltonian simulations into smaller, gate level bodies, and through this, should be able to simulate the time evolution of a quantum system faster than with DCQO.

IV. Computational Requirements

We will aim to replicate the conditions of the paper by mimicking the hardware referenced in the paper, primarily the use of the AWS p4d.24xlarge (A100), p5en.48xlarge (H200) and P6-b200.48xlarge (B200) instances which will allow the use of N greater than 37, more than typical models which are referenced as being 20. The quantum component must show repeated execution of shallow, low N , parameterized circuits for small-to-moderate problem sizes (typically $N \leq 20$ qubits). The solver requires GPU-accelerated quantum circuit simulation using CUDA-Q backends. The system supports parameterized circuits to enable batching over mixer configurations, angle parameters, and independent circuit instances. This allows for efficient sampling of shallow circuits ($p = 1-3$) with moderate shot counts and CPU backend execution for validation and testing. The quantum workload has many independent shallow circuits, making it well-suited for GPU parallel computation. Emphasis is placed on throughput rather than deep-circuit

fidelity, which takes longer.