Introduction and Background

The High-Luminosity Large Hadron Collider (HL-LHC) will push particle collision rates and tracker hit densities well beyond today's experience, creating severe challenges for real-time and offline track reconstruction. Recent graph-based methods—such as the GNN4ITk pipeline developed for the ATLAS Inner Tracker—have shown that machine learning can achieve per-edge classification efficiencies above 98% even at an average of 200 simultaneous collisions [1]. Similarly, GPU-friendly "segment linking" techniques have demonstrated performance on par with CMS's CPU-based chains by forming short stubs locally and then linking them under kinematic constraints. These promising results indicate a path forward, but they leave room for further gains by reducing redundant exploration, exploiting more powerful heuristics, and tapping the nascent potential of quantum devices.

Aim and Approach

We propose a unified framework in Python that unites three complementary innovations to accelerate track building without losing resolution:

1. **Collaborative, Parallel Track Construction**
   As each track hypothesis grows through the detector layers, it will publish a brief "fit-quality" score into a shared, thread-safe data store. Peers can read these scores in real time: if one hypothesis falls well below the emerging best, it stops extending immediately. This approach builds on the same parallel Kalman-filter ideas used in mkFit's SIMD/vectorized loops on CPUs and GPUs [2], but adds live sharing of partial fit metrics so that only the most promising paths consume resources, greatly reducing redundant calculations.

2. **Adaptation of Underexplored Heuristic and Matching Algorithms**
   Beyond A* and bidirectional search, we will adapt and explore multiple meta-heuristic and combinatorial-optimization routines that, despite foundational studies, have never been scaled for HL-LHC track building, some examples are:
   - **Ant Colony Optimization (ACO)** uses virtual "pheromone" trails to bias path growth toward high-quality sequences [3].
   - **Particle Swarm Optimization (PSO)** treats each track hypothesis as a particle guided by its own and the swarm's best solutions [4].
   - **Simulated Annealing (SA)** allows probabilistic uphill moves in a global cost landscape, escaping local minima via a cooling schedule [5].
   - **Genetic Algorithms (GAs)** evolve populations of track parameter sets via crossover and mutation, drawing on Goldberg's canonical work [6].
   - **Best-First / A*** grows only the most promising seed extension first, using physics-informed heuristics to minimize explored branches.
   - **Hungarian Assignment** solves hit-to-track matching in one optimal sweep, replacing iterative greedy steps [7].

   Although early studies in the 1990s touched on SA and GAs with toy detectors, they did not address HL-LHC pileup or exploit modern parallel hardware. Our work will parallelize these methods across CPU cores and GPU blocks, embed them directly in the cooperative growth loops, and apply them to realistic detector geometries and hit densities.

3. **Quantum-Parallel Proof of Concept**
   We will cast a reduced-size seed selection (~10-20 hits) as a QUBO and run it on available quantum annealers or gate-model simulators. Early studies have shown that quantum pattern-recognition routines can compete with classical baselines for charged-particle reconstruction [8]. We will benchmark seed-selection quality, wall-clock time, and resource usage against our classical implementations.

Taken together, these innovations promise to eliminate redundant branch building, harness new algorithmic paradigms, and open the door to hybrid classical–quantum pipelines—pushing HL-LHC tracking closer to real-time, high-accuracy performance.

Broad 12-Week Plan

Phase	Activities
Weeks 1-2	Survey current pipelines (GNN4ITk, mkFit, segment linking); define shared-state design.
Weeks 3-5	Build cooperative growth prototype; integrate vectorized Kalman loops with inter-seed pruning.
Weeks 6-8	Add a few unexplored/underexplored algorithms, potentially: ACO, PSO, SA, GA, best-first/A*, and Hungarian modules; compare on small simulated events.
Weeks 9-10	Formulate QUBO for seed selection; execute quantum annealing and quantum-ML SVM trials.
Weeks 11-12	Collect physics (efficiency, fake-rate) and timing metrics, draft a concise report with figures, and ensure code is documented

Deliverables and Impact

By week 12, we will have a unified Python framework where cooperative parallel growth, six adapted meta-heuristics, and a small-scale quantum prototype coexist and can be used independently. Detailed benchmarks will reveal the trade-offs between speed, accuracy, and resource consumption for each approach under HL-LHC-like conditions. A clear and focused report—including figures, tables, and performance comparisons—will be prepared to document the work. This work will demonstrate that by combining collaborative seed sharing, fresh heuristic methods, and exploratory quantum acceleration, we will demonstrate whether these algorithms are feasible alternatives to existing methods for track reconstruction.

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