Hybrid ML Scheduler - Project Documentation

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1. Executive Summary

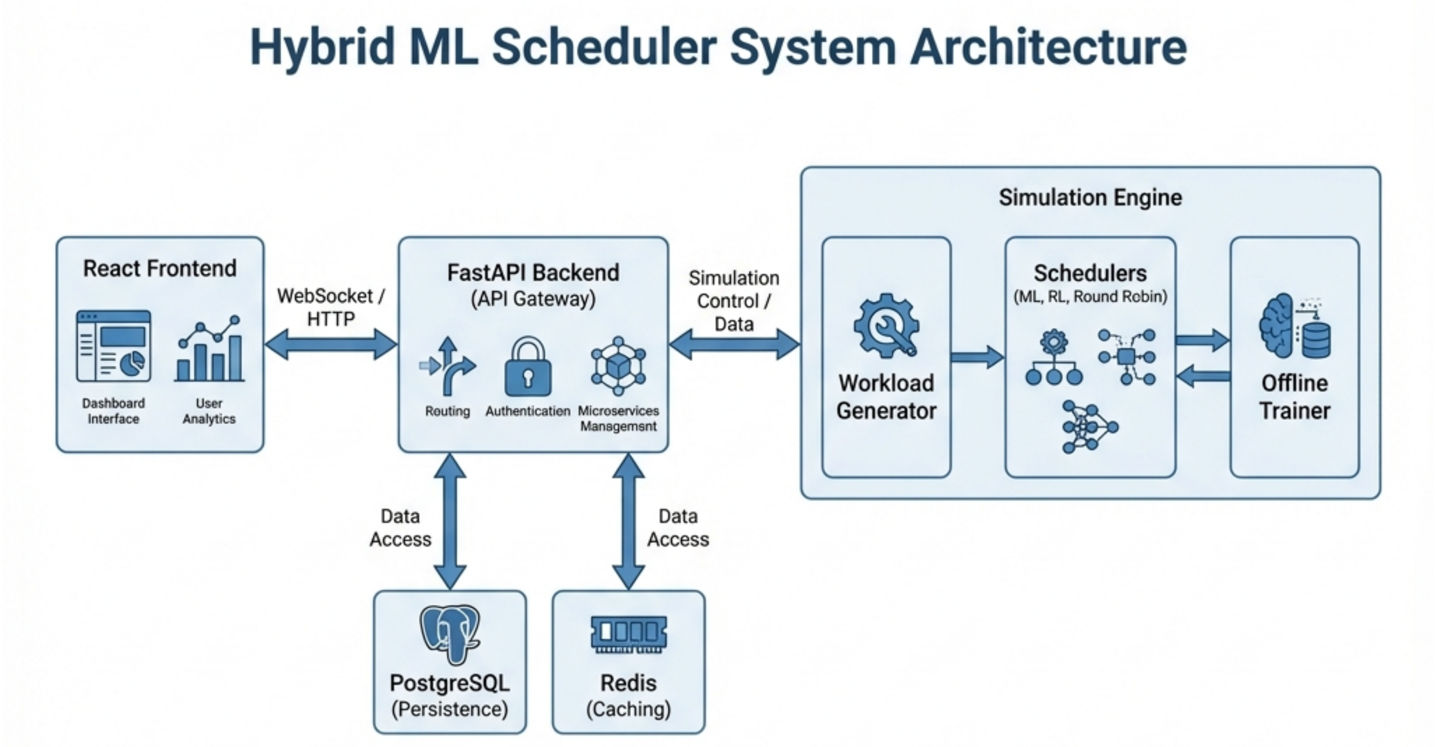
The **Hybrid ML Scheduler** is an advanced simulation and scheduling system designed to optimize task allocation in heterogeneous computing environments (CPU + GPU). It leverages **Machine Learning (Random Forest)** and **Reinforcement Learning (DQN)** to make intelligent scheduling decisions that balance execution time, energy consumption, and cost.

The system features a continuous simulation engine, a robust backend API, persistent storage, and a real-time interactive dashboard for visualization and analysis.

2. System Architecture (High-Level Design)

The system follows a modern, modular architecture composed of four main layers:

1. **Presentation Layer (Frontend):** A React-based dashboard for real-time monitoring and control.
2. **Application Layer (Backend):** A FastAPI server handling API requests, WebSocket streaming, and business logic.
3. **Simulation Layer (Engine):** A Python-based engine that generates workloads and executes scheduling strategies.
4. **Data Layer (Persistence):** PostgreSQL for long-term storage and Redis for high-speed caching.



Data Flow Overview

1. **Workload Generation:** The Simulation Engine generates synthetic tasks with varying characteristics (size, compute intensity, memory).
2. **Scheduling:** Tasks are processed by multiple schedulers in parallel (Round Robin, Random, Greedy, Hybrid ML, RL Agent, Oracle).
3. **Execution Simulation:** A Virtual Cluster model estimates execution time and energy based on the scheduling decision.
4. **Data Persistence:** Results are saved to PostgreSQL via the Backend API. Training data is buffered and stored.
5. **Model Retraining:** The Offline Trainer periodically retrains the ML model using the latest historical data from the database.
6. **Visualization:** The Backend broadcasts real-time updates via WebSockets to the Frontend Dashboard.

3. Deep Dive: Core Logic & Algorithms

This section explains the internal mechanics of the system, allowing you to understand the "how" and "why" without reading the code.

3.1. Workload Generation (The "Tasks")

The system generates a continuous stream of synthetic tasks that mimic real-world parallel computing jobs.

- **Generation Process:** Tasks arrive according to a **Poisson Process** (exponentially distributed inter-arrival times), creating a realistic, bursty workload.
  Task Attributes:
  - **Size (N):** The magnitude of the problem (100 - 5000 units).
    Compute Intensity (I): A value between 0.0 and 1.0 indicating how much the task benefits from parallelization.
    - $I \approx 1.0$: Highly parallelizable (Matrix Multiplication, Deep Learning).
    - $I \approx 0.0$: Serial (I/O bound, recursive logic).
  - **Memory Required (M):** RAM usage (10 - 500 MB).
- **Duration Model:** The estimated base duration is calculated as: $$ T_{base} \propto \frac{N^{1.5}}{I + 0.5} $$ *This means larger tasks take super-linearly longer, but high compute intensity reduces time (assuming parallel hardware).*

3.2. The Schedulers (The "Competitors")

The system runs six scheduling strategies in parallel for every task to compare their performance.

1. Round Robin (Baseline)

- **Logic:** Alternates blindly between resources.
- **Behavior:** Task i goes to GPU, Task $i+1$ goes to CPU.
- **Pros/Cons:** Simple but inefficient; sends GPU-hostile tasks to GPU and vice versa.

2. Random (Baseline)

- **Logic:** Assigns a random fraction of the task to the GPU (0.0 to 1.0).
- **Pros/Cons:** Acts as a stochastic baseline to prove that other methods are learning.

3. Greedy (Heuristic)

- **Logic:** Uses the task's **Compute Intensity** directly as the GPU fraction.
- **Formula:** $Fraction_{GPU} = Intensity$
- **Rationale:** High intensity tasks *should* go to GPU. This is a strong heuristic baseline.

4. Hybrid ML (The "Brain")

- **Type:** Supervised Learning (Random Forest Regressor).
  Features:
  - Raw: `Size`, `Intensity`, `Memory`.
  - Derived: `Memory per Unit Size`, `Compute to Memory Ratio`.

  Logic:
  1. Predicts the **Optimal GPU Fraction** (y) that minimizes execution time.

2. Selects the specific GPU ID that minimizes a weighted cost of **Time** and **Energy**.

- **Training:** Retrains every 50 tasks using a sliding window of the last 1000 "Oracle" decisions.

5. RL Agent (Deep Q-Network)

- **Type:** Reinforcement Learning (DQN with Dueling Architecture).
- **State:** Vector $[Size, Intensity, Memory]$.
- **Action Space:** Discrete choices: ${CPU, GPU_0, GPU_1, GPU_2, GPU_3}$.
- **Reward Function:** Negative weighted sum of Time and Energy. $$ R = - (0.5 \times Time + 0.5 \times Energy) $$
- **Learning:** Uses "Experience Replay" to learn from past mistakes and optimizes its policy to maximize long-term rewards.

6. Oracle (The "Ground Truth")

- **Logic:** A theoretical solver that "cheats" by trying every possible split (0% to 100% in 5% steps).
- **Purpose:** It finds the absolute mathematical minimum execution time for a task.

  Usage:
  - Acts as the **Label** for the Hybrid ML model (Supervised Learning).
  - Serves as the **Performance Ceiling** (100% Efficiency) for comparison.

3.3. Simulation Physics

How do we calculate "Time" and "Energy"?

Execution Time:

- **CPU Time:** Base duration.
- **GPU Time:** $\frac{Base Duration}{Speedup} + TransferTime$
- **Speedup:** $1.0 + (3.0 \times Intensity)$ (Max 4x speedup for high intensity).
- **Transfer Time:** $\frac{Memory}{Bandwidth}$ (Simulating PCIe bottlenecks).

Energy Consumption:

- **GPU Power:** 50W (Active).
- **CPU Power:** 30W (Active).
- $Energy (Joules) = Power \times Time$.

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4. System Flow & Architecture

4.1. The "Loop"

1. **Generate:** A new task is born (`WorkloadGenerator`).
2. **Broadcast:** The task is sent to all 6 schedulers simultaneously.
3. **Decide:** Each scheduler makes its move (Predict, Randomize, or Calculate).
4. **Simulate:** The `VirtualMultiGPU` calculates the *result* (Time, Energy) for each decision.
5. **Persist:** Results are saved to PostgreSQL.

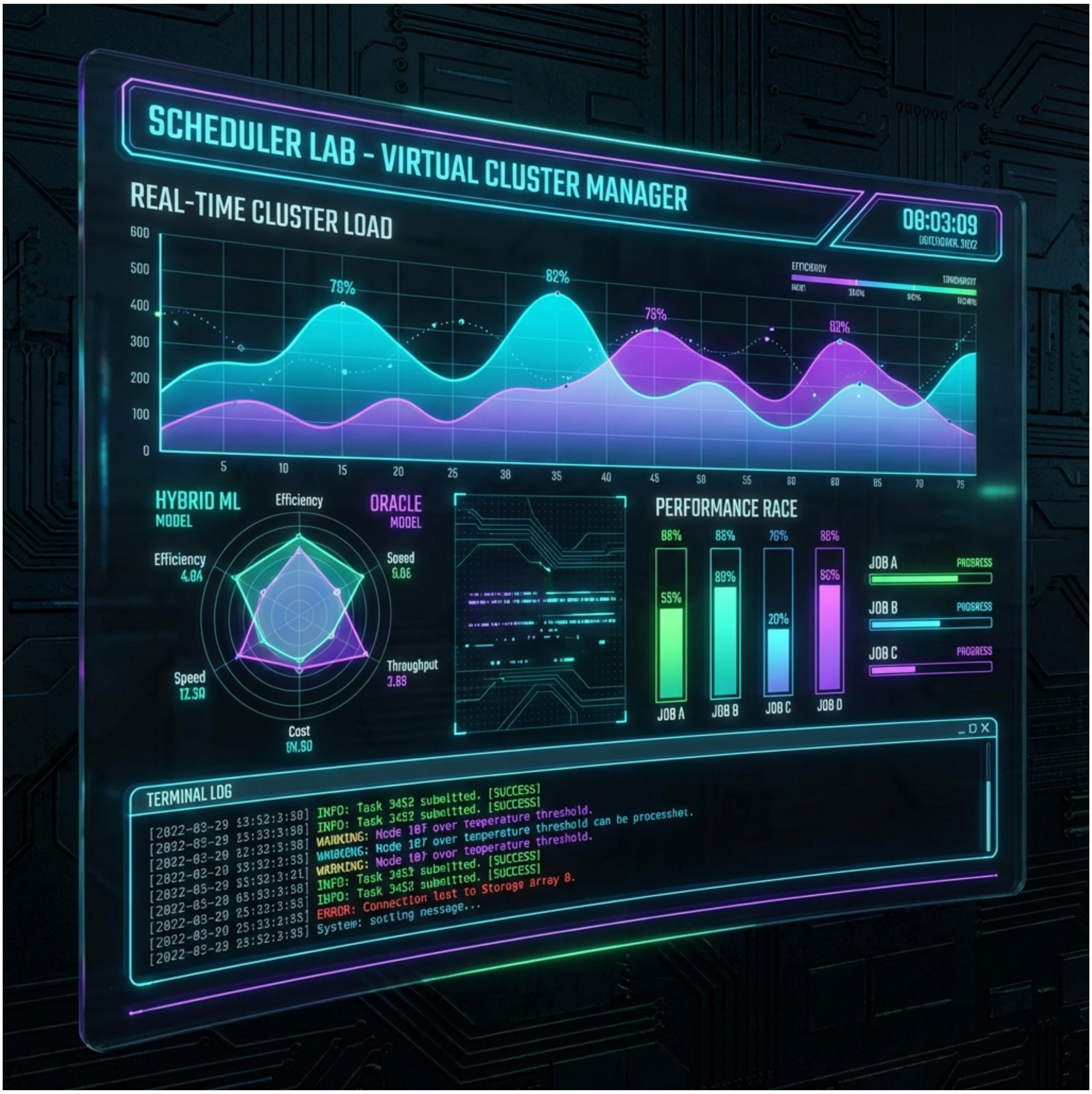
   Learn:
   - **Hybrid ML:** If 50 tasks have passed, fetch history -> Retrain Random Forest.
   - **RL Agent:** Store transition -> Update Q-Network weights.

7. **Visualize:** Send JSON packet via WebSocket to the Dashboard.

4.2. Component Details

Frontend Dashboard (`/dashboard`)

- **Tech:** React, Vite, TailwindCSS, Recharts.
  Key Views:
  - **Performance Race:** A live bar chart where shorter bars = faster schedulers.
    Enhanced Analytics:
    - **Heatmap:** Shows which tasks (Size vs. Intensity) perform best on GPU.
    - **Win/Loss Matrix:** How often Scheduler A beats Scheduler B.
    - **State Management**: Uses React `useState` and `useEffect` for real-time data updates.



```
[2022-83-29 13:52:3:38] INFO: Task 3452 subeltted. [SUCCESS]
[2032-89-29 25:33:3:98] INFO: Task 3452 subeltted. [SUCCESS]
[2022-83-20 22:32:3:38] WARNING: Node 187 over temperature threshold.
[2822-02-20 33:32:2:33] WARNING: Node 187 over tenperature threshold can be processhet.
[2822-03-29 55:32:3:21] WARNING: Node 187 ovor teoperature threshold.
[2832-85-29 65:33:3:98] INFO: Task 3452 subeltted. [SUCCESS]
[2022-85-20 25:22:3:58] INFO: Task 3452 subeltted. [SUCCESS]
[2022-83-29 25:33:2:35] ERROR: Connection lest to Storage array 8.
[2022-03-29 25:33:2:33] System: socting nessage...
[2022-89-29 23:52:3:33]
```

Backend Server (`/backend`)

- **Tech:** FastAPI, Uvicorn, SQLAlchemy (Async), Pydantic.
- **Role:** The central nervous system. It orchestrates the simulation, manages the DB connection, and serves the API.
- **Security:** Implements Rate Limiting (Redis) and Input Validation to protect the system.

Data Layer

- **PostgreSQL:** Stores the "Truth". Every single task execution is logged here.
- **Redis:** The "Short-term Memory". Caches high-speed data like current stats to prevent DB overload.

5. Technical Reference

5.1. Database Schema (PostgreSQL)

The system uses a relational schema optimized for time-series performance.

`tasks` Table

Stores metadata for every generated task.

Column	Type	Description
`task_id`	Integer (PK)	Unique identifier for the task.
`size`	Float	Problem size ($N$).
`compute_intensity`	Float	Parallelizability factor ($0.0 - 1.0$).
`memory_required`	Float	RAM required in MB.
`arrival_time`	Float	Simulation timestamp of arrival.
`dependencies`	JSONB	List of parent task IDs.

`scheduler_results` Table

Logs the outcome of every scheduling decision.

Column	Type	Description
`id`	Integer (PK)	Unique result ID.
`task_id`	Integer (FK)	Reference to the task.
`scheduler_name`	String	Name of the strategy (e.g., 'hybrid_ml').
`gpu_fraction`	Float	Allocated GPU portion ($0.0 - 1.0$).
`actual_time`	Float	Execution time in seconds.
`energy_consumption`	Float	Energy used in Joules.
`execution_cost`	Float	Cost in USD.

`training_data` Table

Historical data used to train the Hybrid ML model.

Column	Type	Description
`size`	Float	Task size.
`compute_intensity`	Float	Task intensity.
`optimal_gpu_fraction`	Float	**Label:** The best fraction found by Oracle.
`optimal_time`	Float	The execution time achieved by Oracle.

5.2. API Specification (FastAPI)

Simulation Control

- `POST /api/simulation/start`: Begin the continuous simulation.
- `POST /api/simulation/stop`: Gracefully stop the engine.
- `POST /api/simulation/pause`: Temporarily halt task generation.
- `GET /api/simulation/status`: Get current stats (tasks processed, running state).

Data & Metrics

- `GET /api/full_history`: Retrieve the latest 1000 training records (used for charts).
- `GET /api/metrics`: Expose Prometheus-formatted metrics for scraping.
- `GET /api/health`: Check connectivity to PostgreSQL and Redis.

WebSocket (`/ws`)

- **Protocol:** JSON over WebSocket.
  Events:
  - `simulation_update`: Real-time packet with current task, scheduler results, and cluster utilization.
  - `notification`: System alerts (e.g., "Model Retrained").

5.3. Configuration Management

The system is configured via environment variables (using `pydantic-settings`).

Key Variables (`.env`)

Variable	Default	Description
`ENVIRONMENT`	development	App environment (dev/prod).
`POSTGRES_HOST`	localhost	Database host.
`POSTGRES_DB`	hybrid_scheduler_db	Database name.
`REDIS_HOST`	localhost	Redis cache host.
`NUM_GPUS`	4	Number of virtual GPUs to simulate.
`RETRAIN_INTERVAL`	50	Tasks between model updates.

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6. Directory Structure

```
hybrid_ml_scheduler/ ■■■ backend/ # FastAPI Application ■ ■■■ api/ # Routes and
Controllers ■ ■■■ core/ # Config and DB setup ■ ■■■ middleware/ # Rate Limit,
Security ■ ■■■ models/ # SQLAlchemy & Pydantic models ■ ■■■ services/ # Business
Logic (Data, Cache) ■■■ dashboard/ # React Frontend ■ ■■■ src/ ■ ■ ■■■ components/
# Reusable UI widgets (Charts) ■ ■ ■■■ App.jsx # Main Dashboard View ■■■ src/ #
Simulation Engine ■ ■■■ simulation_engine.py # Main Loop ■ ■■■ online_scheduler.py #
Hybrid ML Logic ■ ■■■ dqn_scheduler.py # RL Logic ■ ■■■ workload_generator.py # Task
Factory ■■■ scripts/ # Utility Scripts (Init DB, Verify) ■■■ tests/ # Unit and
Integration Tests
```
