Hanzo HMM: Hamiltonian Market Maker for Decentralized AI Compute Exchange

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Abstract

We present **Hanzo HMM** (Hamiltonian Market Maker), an automated market maker for pricing heterogeneous AI compute resources via conserved Hamiltonian invariants. Unlike traditional AMMs which handle fungible tokens, HMM prices multi-dimensional resource bundles (GPU-hours, memory, bandwidth, storage) with quality-weighted pools and SLA-aware routing. Key contributions: (i) Hamiltonian invariant $\mathcal{H}(\boldsymbol{\Psi}, \boldsymbol{\Theta}) = \kappa$ enabling oracle-free pricing, (ii) risk-adjusted fee structure $f = f_m + f_r(\|\Delta\boldsymbol{\Psi}\|)$ for inventory management, (iii) PoAI integration for verifiable job settlement, and (iv) liquidity routing toward high expected-free-energy policies. Testnet deployment demonstrates **¡ 200ms quote latency**, **98.7% price stability** (vs 89.2% for oracle-based), and **15.3% higher capital efficiency** vs traditional orderbook markets.

1 Introduction

Decentralized AI compute markets face unique challenges: resources are heterogeneous (GPU types, memory, network), jobs have complex SLA requirements (latency, locality, privacy), and pricing must react to rapidly changing supply/demand without fragile oracles.

Our Solution. Hanzo HMM treats compute resources as a multi-dimensional asset with Hamiltonian dynamics. By enforcing an invariant $\mathcal{H} = \kappa$, we obtain endogenous prices that clear markets without external feeds. Integration with PoAI enables verifiable job execution and attestation-based quality weighting.

2 Hamiltonian Market Maker (HMM)

2.1 Invariant and State

Let reserve vector $\boldsymbol{R} = (\Psi, \Theta)$ denote effective supply of compute capacity Ψ (e.g., GPU-seconds weighted by quality) and an aggregate demand credit pool Θ. A minimal HMM uses the **bilinear** Hamiltonian

$$\mathcal{H}(\Psi, \Theta) = \Psi\,\Theta = \kappa, \quad \kappa > 0, \tag{1}$$

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which matches the constant-product AMM as a special case. For multi-asset resources $\boldsymbol{\Psi} = (\Psi_1, \ldots, \Psi_m)$ and credits $\boldsymbol{\Theta}$, we use

$$\mathcal{H}(\boldsymbol{\Psi}, \boldsymbol{\Theta}) = \sum_{i=1}^{m} w_i \, \Psi_i \, \Theta_i + \lambda \sum_{i=1}^{m} \tfrac{1}{2}(\Psi_i^2 + \Theta_i^2), \quad w_i, \lambda > 0. \tag{2}$$

The quadratic term controls curvature (inventory risk), yielding smoother quotes.

2.2 Prices, Flows, and Fees

Define the conjugate price for compute class i:

$$p_i \equiv \frac{\partial \mathcal{H}/\partial \Psi_i}{\partial \mathcal{H}/\partial \Theta_i} = \frac{w_i \, \Theta_i + \lambda \, \Psi_i}{w_i \, \Psi_i + \lambda \, \Theta_i}. \tag{3}$$

A swap $\Delta\boldsymbol{\Theta} < 0, \Delta\boldsymbol{\Psi} > 0$ (buy compute) preserves $\mathcal{H}$ up to fee f. We charge a split fee $f = f_m + f_r$: market fee f_m (LP/treasury) and *risk fee* $f_r \propto \|\Delta\boldsymbol{\Psi}\|$ to compensate inventory risk. In continuous time, inventory evolves via

$$\dot{\Psi}_i = s_i - u_i, \quad \dot{\Theta}_i = d_i - v_i, \quad \text{s.t. } \frac{d}{dt}\mathcal{H}(\boldsymbol{\Psi}, \boldsymbol{\Theta}) = 0 \, (\text{net of fees}) \tag{4}$$

with supply inflow s_i (workers) and demand d_i (jobs). Stability follows from convexity of $\mathcal{H}$ in each orthant and fee dissipation.

2.3 Composable Market Objects

Each resource class instantiates an HMM pool; cross-resource jobs route via a *path solver* minimizing total cost under $\mathcal{H}$-preserving constraints. Jobs specify an SLA vector (latency, jitter, region), encoded as Lagrange multipliers in the solver; quotes reflect SLA shadow prices.

3 Proof of AI (PoAI) and Job Settlement

3.1 Task Lifecycle

(1) Client escrows \$AI and mints a credit $\Delta\Theta$. (2) Router clears against HMM to allocate $\Delta\Psi$. (3) Workers execute and emit *attestations*: TEE report + Merkle commitments of I/O + optional succinct proof. (4) Verifiers sample-check; (5) Settlement releases \$AI to workers, rebates unused capacity to pool, distributes fees.

3.2 Attestation Primitives

TEE path: enclave measurements + signed runtime traces. *ZK path:* SNARK-friendly kernels for small circuits; *Batch audit:* randomized canary prompts or seed-replay for LLM inference. Misbehavior triggers slashing and denial windows.

3.3 Closed-Form Expert Weights from PoAI

For each expert m, let $q_m \in [0, 1]$ denote the Bayesian reliability (precision) estimated from historical attestations. Under a PoE framework, the optimal weight follows:

$$\eta_m \propto \frac{q_m}{1 - q_m}, \tag{5}$$

yielding precision-weighted combination. This emerges naturally from Bayesian reliability models and provides a principled, closed-form solution for expert weighting without manual tuning.

4 Token Economics ($AI)

4.1 Utility

$AI is the protocol token for staking, market fees, job settlement, and governance. *Compute credits* Θ are minted by locking $AI at current HMM rate and burned on settlement.

4.2 Emissions and Rewards

Per block, distribute R $AI: validators βR, workers γR pro-rata verified work, curators δR by experience quality shares, treasury $(1 - \beta - \gamma - \delta)R$. A PoAI bonus applies: for job j with value V_j and verified cost K_j, reward ρV_j ($\rho \leq 0.1$) split among parties. Slashing burns a fraction σ of bonds on fraud.

4.3 Fees and Burns

HMM fees split to LPs and treasury; a fixed fraction ζ of market fees is burned to offset emissions. Experience submissions pay a deposit D; refunds scale with measured utility.

4.4 Default Parameters (Initial Mainnet)

Symbol	Meaning	Default
f_m	market fee	30 bps
f_r	risk fee coeff.	5–20 bps per % inventory move
λ	curvature	0.05
β, γ, δ	emissions split	0.35/0.50/0.10
ζ	fee burn	0.25
D	registry bond	25 $AI

5 System Architecture

5.1 Components

- **Workers:** Provide compute capacity (GPU, CPU, RAM, bandwidth, storage)
- **Clients:** Request jobs, escrow $AI, mint demand credits Θ
- **Routers:** Match jobs to resources via path solver
- **HMM Pools:** Per-resource-class pools with Hamiltonian invariant
- **Registry:** On-chain job specs, attestations, settlements
- **Validators:** PoAI verification, slash malicious actors

5.2 Job Lifecycle

1. Client locks \$AI collateral, mints credits $\Delta\Theta$
2. Router queries HMM for quote: $\Delta\Psi$ resources at price p
3. Client accepts, credits locked, $\Delta\Psi$ allocated
4. Workers execute job, emit TEE attestation + outputs
5. Verifiers sample-check attestation quality
6. Settlement: release \$AI to workers, rebate unused Θ, distribute fees

6 Multi-Asset Routing

6.1 Resource Vectors

Jobs specify requirements $\boldsymbol{r} = (r_{\text{gpu}}, r_{\text{vram}}, r_{\text{cpu}}, r_{\text{net}}, r_{\text{disk}})$ plus SLA constraints $\boldsymbol{c}$ (latency $\leq l_{\max}$, region $z \in \mathcal{Z}$, privacy tier).

6.2 Path Solver

Given current reserves $\boldsymbol{\Psi}$ and credits $\boldsymbol{\Theta}$, solve:

$$\min_{\Delta\boldsymbol{\Psi},\Delta\boldsymbol{\Theta}} \quad \sum_i p_i \Delta\Psi_i \tag{6}$$

$$\text{s.t.} \quad \mathcal{H}(\boldsymbol{\Psi} - \Delta\boldsymbol{\Psi}, \boldsymbol{\Theta} + \Delta\boldsymbol{\Theta}) = \kappa, \tag{7}$$

$$\Delta\Psi_i \geq r_i, \quad \forall i, \tag{8}$$

$$\text{SLA constraints } \boldsymbol{c} \text{ satisfied.} \tag{9}$$

This is a convex program (HMM is convex); Lagrange multipliers interpret as SLA shadow prices.

6.3 Quality Weighting

Worker supplies weighted by historical performance $q_j \in [0, 1]$:

$$\Psi_i^{\text{eff}} = \sum_{j:\text{worker } j \text{ offers resource } i} q_j \cdot \Psi_{ij}. \tag{10}$$

Quality scores updated via PoAI attestations (see §**??**).

7 Risk Management

7.1 Inventory Risk

Large swaps ($|\Delta\boldsymbol{\Psi}| \gg \boldsymbol{\Psi}$) deplete reserves, increasing price slippage. The risk fee:

$$f_r = \lambda_r \cdot \frac{\|\Delta\boldsymbol{\Psi}\|_2}{\|\boldsymbol{\Psi}\|_2}, \tag{11}$$

compensates LPs for temporary illiquidity. Default $\lambda_r = 0.02$ (2% per 100% inventory move).

7.2 Dynamic Curvature

The quadratic term in $\mathcal{H}$ adjusts based on volatility:

$$\lambda(t) = \lambda_0 \cdot (1 + \alpha \cdot \mathrm{Vol}_{7d}(\Delta \boldsymbol{\Psi})), \tag{12}$$

where Vol_{7d} is 7-day rolling volatility. This smooths prices during high-frequency trading.

8 Liquidity Provision

8.1 LP Shares

LPs deposit $(\Delta\Psi_i, \Delta\Theta_i)$ and receive shares s:

$$s = \sqrt{\Delta\Psi_i \cdot \Delta\Theta_i} \quad \text{(geometric mean)}. \tag{13}$$

Fees accrue to (s/S_{total}) share of pool reserves.

8.2 Impermanent Loss

For constant-product HMM ($\Psi\Theta = \kappa$):

$$\mathrm{IL} = \frac{2\sqrt{r}}{1+r} - 1, \quad r = \frac{p_{\text{final}}}{p_{\text{initial}}}. \tag{14}$$

Higher λ (curvature) reduces IL but increases slippage.

8.3 Expected Free Energy Weighting

Route liquidity toward policies with high EFE (see PoAI paper):

$$\eta_\pi = \frac{e^{\beta \cdot \mathrm{EFE}(\pi)}}{\sum_{\pi'} e^{\beta \cdot \mathrm{EFE}(\pi')}}, \tag{15}$$

where $\mathrm{EFE}(\pi) = \mathbb{E}[\Delta I + \Delta U - \lambda_c \cdot \mathrm{cost}]$. This incentivizes compute for high-information-gain tasks.

9 Experimental Evaluation

9.1 Testnet Deployment

Deployed on Hanzo testnet (10 validator nodes, 50 worker nodes, 100 client agents).

Metric	HMM	Oracle-based AMM
Quote latency	182ms	341ms
Price stability (7d)	98.7%	89.2%
Capital efficiency	15.3% higher	baseline
LP impermanent loss	2.8%	4.1%

Table 1: Performance comparison over 30-day testnet period.

9.2 Stress Testing

Flash crash simulation (50% supply shock):

- HMM recovered to 95% baseline price in 8 minutes
- Oracle-based system required 42 minutes (oracle update lag)
- Zero arbitrage loops in HMM (thanks to risk fees)

10 Security Analysis

10.1 Flash Loan Attacks

HMM's continuous-time dynamics prevent atomic swaps from exploiting price manipulation. Minimum block time (2s) limits frontrunning. Risk fees make sandwich attacks unprofitable.

10.2 Oracle Manipulation

By design, HMM uses no external price feeds for core pricing. Optional TWAP oracles only for cross-chain settlement (secondary market).

10.3 Sybil Resistance (Workers)

Workers stake $AI bonds, weighted by historical quality q_j. Low-quality or malicious workers slashed via PoAI verification.

11 Related Work

AMMs: Uniswap (CPMM), Balancer (weighted pools), Curve (stableswap). **Compute markets:** Golem, iExec, Akash, Render. **Verifiable compute:** TrueBit, zkEVM, TEE attestations. **Hamiltonian mechanics:** Physics-inspired optimization, control theory.

12 Conclusion

Hanzo HMM provides oracle-free, stable pricing for heterogeneous AI compute via Hamiltonian invariants. Integration with PoAI enables verifiable job settlement and quality-weighted liquidity. Testnet results demonstrate superior capital efficiency and price stability vs traditional approaches. Future work includes cross-chain liquidity bridges and privacy-preserving job execution (encrypted TEE attestations).

A HMM Proofs

A.1 No-Arbitrage

For any cycle of swaps $\{\Delta\mathbf{\Psi}^{(k)}, \Delta\mathbf{\Theta}^{(k)}\}$ returning to initial state:

$$\sum_k f_k > 0 \quad \text{(positive fees)}, \tag{16}$$

preventing profitable arbitrage loops. Proof: convexity of $\mathcal{H}$ + risk fees ensure total cost exceeds any gains from price discrepancies.

A.2 Stability (Lyapunov)

Define Lyapunov function $V = |\mathcal{H} - \kappa|^2$. Then:

$$\frac{dV}{dt} = 2(\mathcal{H} - \kappa)\frac{d\mathcal{H}}{dt} \leq -\alpha V \quad (\alpha > 0), \tag{17}$$

implying exponential convergence to $\mathcal{H} = \kappa$ under fee dissipation.

B Solidity Interface

```
interface IHMM {
  struct Pool {
    uint256[] psi;     // Resource reserves
    uint256[] theta;   // Credit reserves
    uint256 kappa;     // Invariant
    uint256 lambda;    // Curvature
    uint256[] weights; // Per-resource weights
  }

  function quoteBuy(uint256 poolId, uint256[] calldata dTheta)
    external view returns (uint256[] memory dPsi, uint256 fee);

  function swap(uint256 poolId, uint256[] calldata dTheta,
    uint256[] calldata minPsi)
    external payable returns (uint256[] memory dPsi);

  function addLiquidity(uint256 poolId, uint256[] calldata dPsi,
    uint256[] calldata dTheta)
    external returns (uint256 lpShares);
}
```

Disclaimer. This document describes a proposed protocol. Security properties require formal verification and audit.