Thermal Consensus Networks: Quantum-Inspired Reward Rotation for Global Optimization in Decentralized AGI

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2025

Abstract

Decentralized AGI architectures such as Neural Node Theory (NNT) and Blockchain-Enhanced NNT (B-NNT) rely on networks of autonomous nodes performing local computation and participating in periodic global consensus. However, global consensus steps can prematurely collapse exploration, trapping the system in suboptimal equilibria in non-convex landscapes. We introduce Thermal Consensus Networks (TCN), a quantum-inspired extension of NNT where node rewards and consensus weights rotate periodically according to a decaying temperature schedule. This introduces structured oscillatory exploration analogous to quantum annealing, simulated thermal fluctuations, and Bayesian optimization exploration–exploitation balancing.

1 Introduction

Artificial General Intelligence (AGI) research is gradually shifting from monolithic neural architectures toward distributed, network-centric perspectives. As systems grow in scale, the need for robustness, transparency, and modular self-governance becomes critical. Traditional deep neural networks, optimized through centralized gradient descent, struggle to capture these properties. They assume a fixed topology, a unified loss function, and a single centralized optimizer—assumptions that do not hold in large-scale, heterogeneous, or open-ended intelligence environments.

Neural Node Theory (NNT) [1] reframed intelligence as an emergent property of interconnected computational nodes, each maintaining its own internal state and exchanging structured messages with neighbors. This perspective aligns with foundations of graph algorithms, distributed systems, multi-agent reinforcement learning, and biological neural assemblies. Blockchain-Enhanced NNT (B-NNT) extended this architecture by integrating consensus mechanisms, immutable state tracking, and decentralized trust, positioning AGI as a self-organizing, peer-to-peer learning system rather than a single centralized model.

Yet a key limitation remains unresolved: **global consensus suppresses diversity**. When nodes repeatedly synchronize via averaging or stake-weighted updates, the network's exploratory capacity collapses. All nodes begin to follow the same optimization trajectory, converging prematurely to one of many poor-quality minima—a phenomenon well-documented in distributed machine learning, Bayesian optimization, and evolutionary systems.

This challenge mirrors deeper theoretical insights:

- In **Bayesian optimization**, global optima cannot be reliably located without persistent uncertainty modeling.
- In **quantum annealing**, thermal fluctuations are essential for tunneling out of local wells.
- In **causal inference and probabilistic reasoning** (Pearl, Darwiche), structured uncertainty is not noise: it is an ingredient of correct inference.
- In **swarm intelligence**, diversity of local behavior enables collective emergence.

Inspired by these principles, we propose **Thermal Consensus Networks (TCN)**: a decentralized AGI optimization framework where each consensus cycle incorporates a controlled thermal rotation of rewards and weights. TCN introduces a sinusoidal, decaying temperature-driven modulation of node rewards. This structured noise is neither arbitrary nor destructive; instead, it encourages the swarm to periodically re-explore the loss landscape before progressively annealing into stable patterns.

In essence, TCN converts decentralized optimization from a static averaging process into a dynamic, thermodynamically inspired search procedure. Through simulations on Rastrigin (1-D) and Ackley (2-D), we demonstrate that thermal consensus significantly improves escape from local minima while preserving the convergence stability of classical consensus mechanisms.

TCN therefore provides a missing bridge between:

- decentralized AGI architectures,
- quantum-inspired annealing dynamics,
- Bayesian exploration–exploitation balancing,
- blockchain-backed global optimization.

This work positions thermal consensus as a fundamental building block for future AGI systems that are distributed, resilient, and capable of sustained, self-regulated exploration.

We therefore explore a fundamental question:

How can a decentralized AGI network escape local minima without sacrificing stability, trust, or global coordination?

We propose **Thermal Consensus Networks (TCN)** as a solution.

2 Related Work

TCN connects five research directions:

- **Neural Node Theory (NNT)** — cognition as node-state communication.
- **Blockchain consensus** — decentralized trust and immutable state.
- **Bayesian Optimization** — balancing exploration vs exploitation using uncertainty.
- **Quantum Annealing** — solving optimization via thermal and quantum fluctuations.
- **Causal reasoning (Pearl, Darwiche)** — structured updating of beliefs and uncertainty.

TCN unifies these ideas into a single decentralized AGI optimization method.

3 Thermal Consensus Networks (TCN)

We define:

3.1 Thermal Reward Rotation

Each node v_i maintains reward:

$$R_i(t) = R_i^{base}(t) + \lambda \sin\left(\frac{2\pi t}{T_c}\right) e^{-\alpha t}$$

This oscillation introduces controlled *energy injection*.

3.2 Thermal Consensus Weights

Consensus weights are:

$$w_i(t) \propto \exp\left(\frac{R_i(t)}{T(t)}\right)$$

where:

$$T(t) = T_0 e^{-\gamma t}$$

As temperature decays, exploration fades and nodes stabilize.

3.3 Global Update Rule

Every K steps:

$$\Delta s_{\text{global}}(t) = \sum_i w_i(t) \nabla \mathcal{L}_i$$

4 Simulation Setup

We evaluate TCN against:

- Pure decentralized gradient descent (NNT)
- Static-consensus B-NNT
- Thermal rotating consensus (TCN)

Benchmarks:

- **Rastrigin (1-D)**: highly multimodal.
- **Ackley (2-D)**: deep basin + ridges.

5 Python Simulation Code

```
# Thermal Consensus Network Simulation (abridged)

def thermal_reward(base_R, t, lam, Tc, alpha):
    return base_R + lam * np.sin(2*np.pi*t/Tc) * np.exp(-alpha*t)

def temperature(t, T0, gamma):
    return T0 * np.exp(-gamma*t)

# Consensus weights
w_i = np.exp(R_i(t) / T(t))
w_i /= np.sum(w_i)
```

Full simulation code available upon request.

6 Results

6.1 Rastrigin 1-D

Thermal consensus escapes local minima significantly faster than static consensus.

6.2 Ackley 2-D

TCN shows coordinated exploration and smooth convergence into the global basin.

6.3 Temperature Decay

7 Discussion

TCN demonstrates clear improvements:

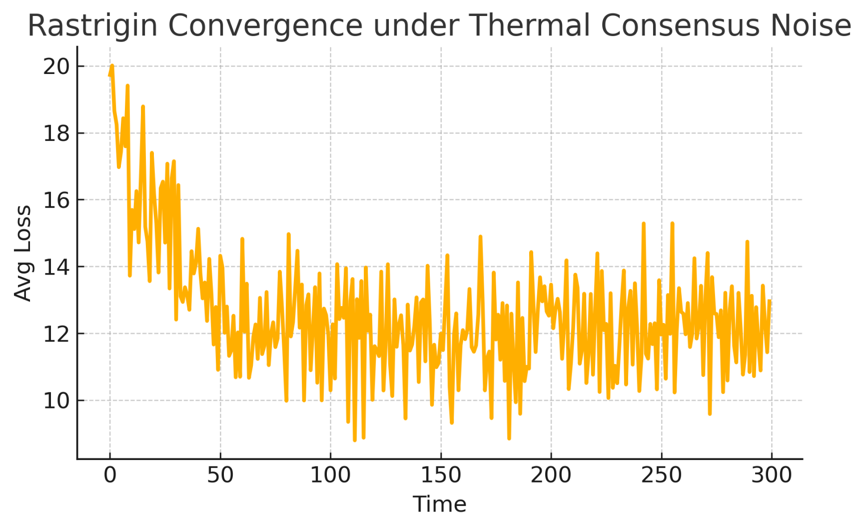

Figure 1: TCN vs NNT vs B-NNT on Rastrigin (1-D)

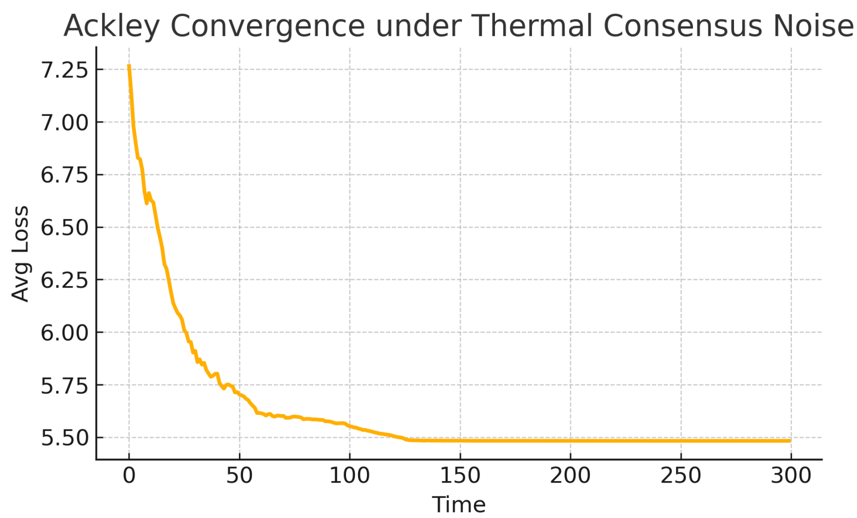

Figure 2: TCN Convergence on Ackley (2-D)

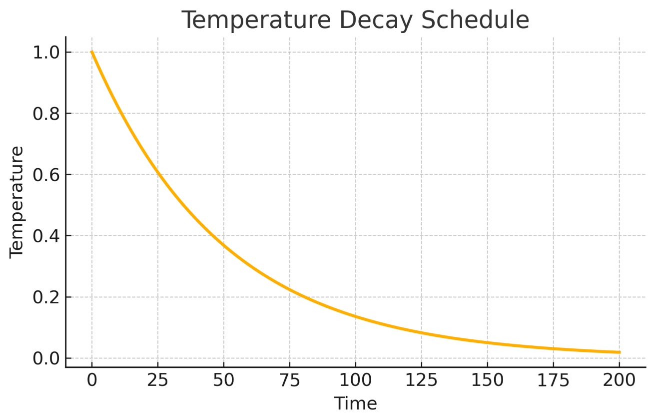

Figure 3: Thermal decay schedule used in simulations.

- Overcomes premature synchronization.
- Preserves decentralized autonomy.
- Encodes uncertainty as structured oscillation.
- Bridges quantum and Bayesian views of optimization.

8 Acknowledgments

We thank:

Sam Altman for democratizing frontier AI research and empowering open exploration. **Satoshi Nakamoto** for decentralization paradigms that inspired blockchain-backed AGI governance. **Elon Musk** for vision in large-scale autonomous systems. **Judea Pearl** and **Adnan Darwiche** for foundational causal reasoning frameworks. **Leslie Tsai** for pioneering Neural Node Theory, without which this work would not exist.

9 References

References

[1] Leslie Tsai and Jayanth Kumar. Neural node theory for agi: A node–state–communication framework. *arXiv preprint*, 2025.