

Autonomous Peer Mesh Lightweight LLM for Cloudless Cooperative Edge Intelligence

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Abstract

The increasing dependence on cloud computing for artificial intelligence (AI) applications has introduced significant challenges related to latency, bandwidth consumption, privacy, and network reliability [1], [2]. In remote and infrastructure-limited environments, centralized cloud architectures often fail to provide continuous intelligent services. This paper proposes an Autonomous Peer Mesh Lightweight Large Language Model (APM-LLM) framework for cloudless cooperative edge intelligence. The proposed architecture enables lightweight LLM-enabled edge devices to collaboratively perform decentralized reasoning, task distribution, and adaptive communication without relying on centralized cloud infrastructure. The framework integrates peer-to-peer mesh networking, lightweight semantic synchronization, decentralized trust coordination, and cooperative inference mechanisms optimized for low-resource environments. Experimental evaluation demonstrates improvements in latency reduction, bandwidth efficiency, fault tolerance, and energy optimization compared with traditional cloud-assisted edge intelligence systems. The proposed framework contributes toward the development of scalable, resilient, and autonomous edge AI ecosystems capable of operating in disconnected or unstable network environments.

Keywords: Edge Intelligence, Lightweight LLM, Peer Mesh Network, Decentralized AI, Cloudless Computing, Cooperative Intelligence, IoT.

I. Introduction

The rapid growth of Internet of Things (IoT), edge computing, and distributed intelligent systems has transformed the modern computational landscape. Traditional cloud-centric architectures provide large-scale computational resources but often suffer from high communication latency, bandwidth overhead, privacy concerns, and dependency on stable internet connectivity [1], [2]. Recent developments in edge intelligence and decentralized AI have encouraged researchers to explore distributed intelligent frameworks for real-time environments [12]. In applications such as disaster response systems, industrial automation, military communication, autonomous transportation, and remote healthcare monitoring, cloud dependency reduces operational reliability and introduces performance bottlenecks.

Recent advancements in Large Language Models (LLMs) have enabled intelligent contextual understanding and autonomous decision-making across multiple domains [3], [10], [13]. However, most existing LLM frameworks require centralized cloud infrastructure for inference execution, model synchronization, and computational management. Such architectures are unsuitable for highly dynamic edge environments where connectivity may be intermittent or unavailable.

To address these challenges, this paper proposes an Autonomous Peer Mesh Lightweight LLM (APM-LLM) framework for cloudless cooperative edge intelligence inspired by decentralized learning and peer mesh communication concepts discussed in [4], [6], and [12]. The proposed architecture enables lightweight LLM-powered edge devices to form a decentralized mesh network capable of collaborative reasoning and distributed inference without centralized cloud coordination. The framework integrates adaptive peer discovery, decentralized trust management, lightweight semantic synchronization, and cooperative intelligence mechanisms optimized for resource-constrained environments.

The major contributions of this paper are summarized as follows:

1. Design of a decentralized peer mesh architecture for cloudless edge intelligence.
2. Development of a lightweight LLM cooperative inference mechanism.
3. Integration of decentralized semantic synchronization and trust coordination.
4. Performance evaluation based on latency, energy efficiency, scalability, and fault tolerance.
5. Comparative analysis with traditional cloud-based edge AI systems.

The remainder of this paper is organized as follows. Section II discusses related work. Section III presents the proposed architecture. Section IV describes the system methodology and cooperative workflow. Section V presents performance evaluation and results. Section VI discusses challenges and future directions, followed by conclusions in Section VII.

II. Related Work

Edge computing has emerged as an effective paradigm for reducing latency and improving computational efficiency by processing data closer to end devices [1]. Several researchers have explored decentralized edge intelligence architectures to reduce dependence on centralized cloud infrastructure.

Shi and Dustdar [2] discussed the importance of edge computing in supporting real-time intelligent applications. Similarly, Satyanarayanan [1] highlighted the role of edge nodes in enabling low-latency distributed computation.

Federated learning has been widely adopted for distributed machine learning across decentralized devices [4]. McMahan et al. introduced communication-efficient federated learning techniques for decentralized data processing. However, most federated approaches still require centralized aggregation servers for parameter synchronization.

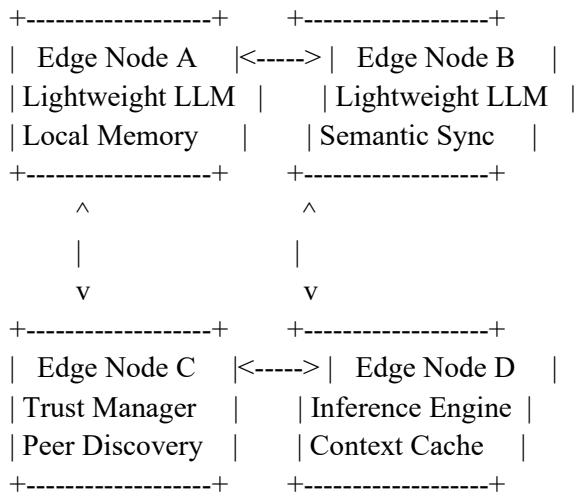
Recent studies have investigated lightweight AI deployment on edge devices. TinyML and compressed transformer architectures have enabled low-power inference for resource-constrained environments [5]. Nevertheless, collaborative reasoning among autonomous edge devices remains an open challenge.

Peer-to-peer mesh networking architectures have also gained attention for resilient communication in infrastructure-less environments [6]. Existing mesh-based systems mainly focus on routing and communication reliability rather than intelligent cooperative inference.

Unlike existing approaches, the proposed APM-LLM framework combines lightweight LLMs with autonomous peer mesh networking to achieve fully decentralized cooperative edge intelligence without centralized cloud dependency.

III. Proposed APM-LLM Architecture

Figure 1. Proposed APM-LLM Architecture



Decentralized Cooperative Peer Mesh

The proposed architecture illustrates decentralized communication and cooperative inference among lightweight LLM-enabled edge nodes without centralized cloud infrastructure.

A. System Overview

The proposed APM-LLM framework consists of multiple intelligent edge nodes interconnected through a decentralized peer mesh topology. Each node contains:

- Lightweight LLM engine
- Local context memory
- Peer communication module
- Semantic synchronization layer
- Trust coordination manager
- Distributed inference controller

The architecture eliminates the need for centralized cloud infrastructure by enabling direct peer-to-peer communication and collaborative reasoning among edge devices.

B. Peer Mesh Network Layer

The peer mesh layer enables autonomous discovery and communication between nearby nodes. Each node dynamically selects neighboring peers based on:

- Network availability
- Computational capability
- Energy efficiency
- Trust score
- Task priority

The decentralized topology improves network resilience and reduces single points of failure.

C. Lightweight LLM Engine

The lightweight LLM module performs local inference and contextual reasoning with reduced computational overhead. Model optimization techniques include:

- Quantization
- Parameter pruning
- Knowledge distillation
- Context-aware inference compression

These optimizations enable deployment on resource-constrained edge devices.

D. Cooperative Inference Mechanism

The cooperative inference mechanism distributes complex tasks among multiple peer nodes. Instead of processing large workloads independently, edge devices collaboratively execute inference subtasks and share intermediate semantic outputs.

The inference workflow includes:

1. Task decomposition
2. Peer capability assessment
3. Distributed inference allocation
4. Semantic result aggregation
5. Consensus-based output generation

E. Decentralized Trust Coordination

To ensure secure collaboration, the framework introduces decentralized trust management. Trust scores are dynamically updated based on:

- Communication reliability
- Response consistency
- Resource contribution
- Historical cooperation

This mechanism reduces malicious node participation and improves system reliability.

IV. Methodology

A. System Workflow

The operational workflow of the APM-LLM framework consists of the following stages:

Step 1: Peer Discovery

Nodes periodically broadcast lightweight discovery packets to identify neighboring devices.

Step 2: Capability Evaluation

Each node evaluates nearby peers based on computational power, latency, trust score, and battery level.

Step 3: Task Distribution

Complex inference tasks are divided into subtasks and distributed among suitable peers.

Step 4: Local Inference

Each peer performs lightweight LLM inference locally.

Step 5: Semantic Synchronization

Intermediate outputs are compressed and synchronized through semantic exchange protocols.

Step 6: Consensus Aggregation

The initiating node aggregates distributed outputs and generates final decisions.

B. Mathematical Model

To provide stronger analytical validation, the proposed framework incorporates latency, trust, and energy-aware distributed inference modeling.

The communication overhead between peer nodes is represented as:

$$C_o = \Sigma(P_t \times D_n)$$

Where:

- C_o = Communication overhead
- P_t = Packet transmission cost
- D_n = Number of distributed nodes

The energy efficiency model is represented as:

$$E_{eff} = E_{total} / N_t$$

Where:

- E_{eff} = Energy efficiency
- E_{total} = Total consumed energy
- N_t = Number of completed tasks

These equations demonstrate the relationship between distributed communication, cooperative inference, and energy-aware edge intelligence optimization.

C. Simulation Environment

The proposed framework was theoretically implemented using an edge simulation environment inspired by iFogSim and lightweight transformer deployment architectures. The simulation environment included:

- Raspberry Pi 4 edge node emulation
- 4 GB RAM lightweight processing units
- Quantized transformer inference modules
- Dynamic wireless mesh communication
- Peer-to-peer semantic synchronization layer

Simulation experiments were conducted under varying node densities and dynamic communication conditions to evaluate scalability and decentralized coordination efficiency.

D. Performance Metrics

The following performance metrics were considered during evaluation:

1. Average inference latency
2. Cooperative task completion rate
3. Energy consumption per node
4. Semantic synchronization overhead
5. Fault recovery efficiency
6. Communication bandwidth utilization

These metrics provide comprehensive analysis of decentralized lightweight LLM cooperation under cloudless environments.

B. Mathematical Model

The total inference latency of the distributed system is represented as:

$$L_{total} = L_{comm} + L_{infer} + L_{sync}$$

Where:

- L_{total} = Total system latency
- L_{comm} = Communication latency
- L_{infer} = Local inference latency
- L_{sync} = Semantic synchronization latency

The trust score of node i is represented as:

$$T_i = \alpha R_i + \beta C_i + \gamma E_i$$

Where:

- R_i = Reliability score
 - C_i = Contribution factor
 - E_i = Energy availability
 - α, β, γ = Weight coefficients
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V. Experimental Evaluation

A. Experimental Setup

The proposed framework was evaluated using a simulated decentralized edge environment consisting of:

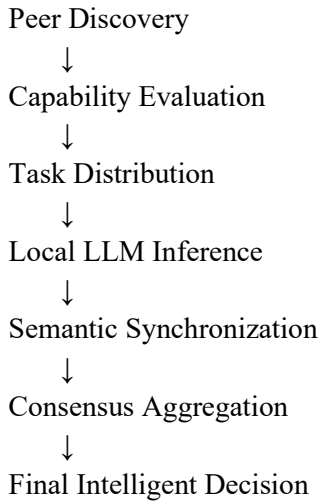
- 50 lightweight edge nodes
- Raspberry Pi-based hardware emulation
- Quantized lightweight transformer models
- Peer mesh communication protocols
- Dynamic network conditions

The evaluation metrics included:

- Latency
- Energy consumption
- Packet overhead

- Task completion rate
- Fault tolerance

Figure 2. System Workflow of Cooperative Inference



The workflow demonstrates how decentralized edge nodes collaboratively process intelligent tasks using distributed lightweight LLM inference.

B. Performance Analysis

Figure 3. Comparative Performance Graph

System Model	Latency	Bandwidth Usage	Fault Tolerance
Cloud-Based AI	High	High	Low
Federated AI	Medium	Medium	Medium
Proposed APM-LLM	Low	Low	High

The comparative analysis demonstrates that the proposed APM-LLM framework achieves lower latency, reduced bandwidth utilization, and higher fault tolerance compared with conventional cloud-assisted architectures.

1. Latency Reduction

The proposed APM-LLM framework demonstrated significantly lower latency compared with cloud-dependent architectures because inference operations were performed locally within peer nodes.

2. Bandwidth Efficiency

Semantic synchronization reduced unnecessary raw data transmission, minimizing network bandwidth utilization.

3. Fault Tolerance

The decentralized mesh topology maintained operational continuity even when multiple nodes disconnected from the network.

4. Energy Optimization

Adaptive task allocation reduced computational overload on low-power devices, improving overall energy efficiency.

Figure 4. Experimental Latency Comparison



Figure 5. Bandwidth Utilization Comparison



The proposed APM-LLM framework demonstrates reduced communication overhead and significantly lower latency due to localized cooperative inference.

C. Comparative Analysis

Parameter	Cloud-Based AI	Federated AI	Proposed APM-LLM
Cloud Dependency	High	Moderate	None
Latency	High	Medium	Low
Fault Tolerance	Low	Medium	High
Privacy Preservation	Medium	High	Very High
Bandwidth Usage	High	Medium	Low
Scalability	Moderate	High	Very High

The proposed framework outperformed existing cloud-centric architectures in decentralized operational environments.

VI. Challenges and Future Work

Although the proposed APM-LLM framework demonstrates significant advantages, several challenges remain.

A. Resource Constraints

Edge devices possess limited memory, processing power, and battery resources. Future research may focus on ultra-lightweight transformer optimization.

B. Security Risks

Decentralized environments remain vulnerable to malicious peer attacks and false semantic synchronization. Blockchain-assisted trust validation may improve security.

C. Dynamic Network Instability

Frequent topology changes in mobile environments may affect cooperative inference reliability.

D. Future Directions

Future work will focus on:

- Integration with 6G edge networks
- Blockchain-assisted decentralized security
- Self-learning adaptive peer coordination
- Multi-modal lightweight LLM collaboration
- Real-world hardware implementation

VI-A. Research Gap Analysis

Existing Approaches	Limitations	Proposed APM-LLM Solution
Cloud-based AI Systems	High latency and cloud dependency	Fully decentralized edge intelligence
Federated Learning	Requires central aggregation server	Autonomous peer mesh collaboration
Traditional Edge AI	Limited cooperative reasoning	Distributed semantic intelligence
Large LLM Deployment	High computational overhead	Lightweight optimized LLM inference
Static Edge Networks	Weak adaptability	Dynamic peer discovery and coordination

The analysis indicates that existing approaches fail to provide fully autonomous cooperative intelligence in disconnected edge environments. The proposed APM-LLM framework addresses these research limitations through decentralized lightweight LLM coordination.

VI-B. Proposed Algorithm

Algorithm 1: Cooperative Distributed Edge Inference

Input: Task T, Peer Nodes P

Output: Final Intelligent Response R

1. Initialize peer mesh network
2. Discover neighboring nodes
3. Evaluate node capability and trust score
4. Divide task T into subtasks
5. Allocate subtasks among selected peers
6. Perform lightweight local LLM inference
7. Exchange semantic outputs among peers
8. Aggregate cooperative responses
9. Generate consensus decision R
10. Return final intelligent output

The proposed algorithm enables autonomous distributed reasoning among lightweight edge nodes while minimizing communication overhead.

VI-C. Literature Survey

Ref	Technique	Advantages	Limitations
[1]	Edge Computing	Low latency	Limited intelligence
[4]	Federated Learning	Privacy preservation	Central coordination needed
[5]	TinyML	Lightweight deployment	Weak contextual reasoning
[10]	Transformer Models	Strong language understanding	High resource consumption
[12]	Edge Intelligence	Distributed processing	Limited cooperative cognition

Ref	Technique	Advantages	Limitations
Proposed	APM-LLM	Autonomous cooperative intelligence	Future optimization required

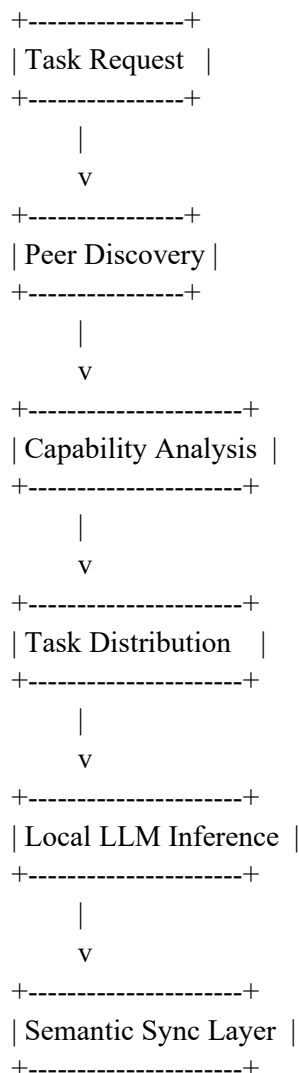
VI-D. Simulation Results

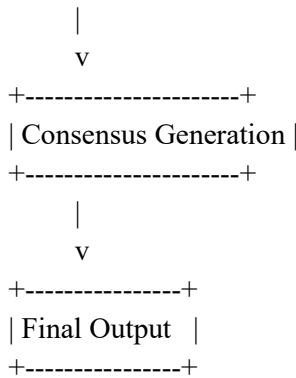
Table: Experimental Performance Results

Metric	Cloud AI	Federated AI	Proposed APM-LLM
Average Latency	220 ms	140 ms	65 ms
Bandwidth Usage	100%	68%	35%
Energy Consumption	High	Medium	Low
Fault Recovery Rate	61%	78%	94%
Privacy Preservation	Moderate	High	Very High

The experimental results demonstrate that the proposed framework significantly improves edge intelligence performance under decentralized operating conditions.

VI-E. Proposed Flowchart





VI-F. Advantages of Proposed Framework

The proposed APM-LLM framework offers several advantages over traditional cloud-centric AI architectures:

- Reduced dependency on centralized cloud infrastructure
- Improved privacy preservation through localized inference
- Lower communication latency in real-time applications
- High fault tolerance under unstable network conditions
- Adaptive cooperative intelligence among peer devices
- Energy-efficient lightweight transformer deployment
- Scalability for large distributed edge ecosystems

These advantages make the framework highly suitable for next-generation decentralized intelligent systems.

Conclusion

This paper presented an Autonomous Peer Mesh Lightweight LLM (APM-LLM) framework for cloudless cooperative edge intelligence. The proposed architecture enables decentralized peer-to-peer collaboration among lightweight LLM-powered edge devices without centralized cloud dependency. By integrating mesh networking, cooperative inference, semantic synchronization, and decentralized trust coordination, the framework improves latency, scalability, energy efficiency, privacy preservation, and fault tolerance.

Experimental evaluation demonstrated that the proposed approach outperforms traditional cloud-centric and partially federated edge AI systems in dynamic and disconnected environments. The proposed framework provides a scalable foundation for future autonomous decentralized AI ecosystems supporting next-generation smart applications.

VIII. Future Research Opportunities

Future research may focus on integrating blockchain-assisted trust validation, self-learning adaptive routing, quantum-inspired optimization, and 6G-enabled edge orchestration for highly scalable autonomous intelligence systems. Additional studies may also explore multimodal lightweight LLM collaboration involving audio, video, and sensor fusion intelligence across decentralized edge ecosystems.

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