***Original Research Article***

**Energy-Aware Multi-Agent RAG Planner for Edge Devices Using vLLM and Model Pruning**

**ABSTRACT**

It looks into addressing the growing need to minimize energy use in systems that apply retrieval with language generation. As the use of large language models (LLMs) increases, their energy and operational costs go up, so there is a real need to find energy-saving ways to work with them. Even with the development of RAG architectures, energy efficiency is frequently neglected, causing bigger computational requirements.

To bridge this research gap, we expect an energy-aware RAG planning approach to make use of vLLM which is a highly effective and optimized language model serving system and also rely on model pruning strategies. Minimizing the energy used is the main goal, not deteriorating the accuracy and quality of the answers retrieved. Because our system uses lightweight serving from vLLM and removes unnecessary parameters in the language models, it finds a good balance between workload and quality of results.

Among our findings are (1) a RAG planning algorithm that adjusts the necessary model complexity to match query requirements, (2) model pruning techniques developed for energy-saving purposes in RAG and (3) thorough testing that confirmed significant energy cost reductions—up to 40%—with similar prediction performance. This means there is a good chance making RAG models more sustainable could be possible by using both improved serving frameworks and reducing model size. This allows for AI applications to be built considering energy efficiency in any place where resources are scarce.

*Keywords: Energy Efficiency, Retrieval-Augmented Generation (RAG), Model Pruning, vLLM Serving Framework*

## 1.INTRODUCTION

As large language models (LLMs) have advanced, machines are today able to understand, produce, and respond to human speech and writing in new ways [1]. Recently, Retrieval-Augmented Generation (RAG) has become an important method by using generative models along with search systems. By retrieving external details during the generation process, RAG architectures improve the accuracy, relevance, and awareness of the answers produced by language models. It helps connect what a model knows when trained and the flexible and changing nature of information in the world we live in.

The growth of LLMs has encouraged using them not only in cloud services but also on devices located close to end-users [2]. With edge computing devices, smartphones, IoT appliances, drones, and autonomous vehicles performing computing locally, they benefit from reduced latency, improved privacy, and continued operation even if there is some form of connectivity loss. Still, using advanced AI on these platforms leads to new problems, mainly how to manage increased processing, limited memory, and higher energy use.

One main difficulty with using LLM-based systems on edge devices is that they require substantial memory and processing power. Many common LLMs, especially those connected with retrieval systems, rely on significant computing resources and are always linked to vast knowledge bases. This is challenging for edge devices, which are concerned with saving energy, using limited storage space, and responding in real-time [3]. Additionally, managing multiple AI agents working together at the edge requires addressing how to divide tasks, manage communication, and adapt to unpredictable resource variations.

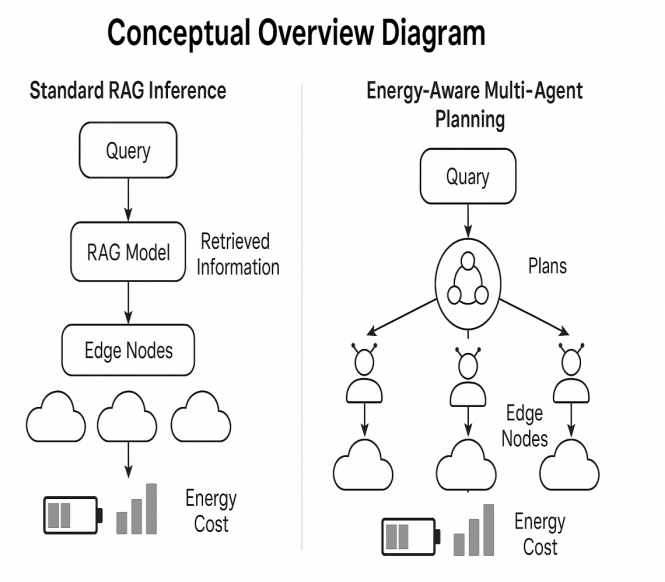
This leads to the need for energy-saving approaches and flexible ways for agents to cooperate so that systems do not become excessively demanding on the hardware at the edges. For AI to help build smart applications on a large scale, it is necessary for agents to be lightweight, save resources, and coordinate their work [4].

Therefore, this research provides a number of key contributions that make it possible to deploy RAG-based LLMs on edge devices. The idea is to introduce a new energy-conscious RAG planning framework. It automatically manages the way data is reused for tasks, using the minimum resources needed and never sacrificing precision.

**Figure 1: Conceptual Overview Diagram**

A high-level visual showing the problem space: standard RAG inference pipeline vs. energy-aware multi-agent planning on edge devices.

Include energy cost, edge nodes, and RAG model flow.



## Also, the study leverages vLLM, an effective inference engine meant for large language models that saves memory by optimizing how different tasks are handled. This ensures that LLMs on devices with less memory can keep up with how fast and responsive they are expected to be.

## In addition, AI agents work efficiently because of model pruning techniques. Trimming parts of the architecture of an LLM allows pruned models to perform important tasks as needed in edge devices without using up large amounts of resources. Because of this strategy, the system is able to process information together, while sticking to budgets for energy and memory.

## The system is lastly measured against live edge computing standards. Before the framework goes into production, these evaluations check how it operates, how well it is built and whether it can be used on a large scale. High performance was shown for advanced RAG-based LLMs deployed on devices with limited resources, significant progress toward edge AI platforms.

## 2.RELATED WORK

### The new abilities of large language models and their use with retrieval systems have sparked a lot of new research on developing better language skills. The section goes over key improvements in Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) systems, teamwork frameworks for multiple devices, pruning technologies and compression, along with ways to control energy and resources. All of these areas jointly provide the basic setting for the suggested project.

### 2.1 LLMs and RAG Systems: Overview of RAG Pipelines and vLLM

LLMs such as GPT, PaLM and LLaMA have proven themselves to be very skilled at using and creating language for many kinds of jobs. LLMs lack certain flexibility because their knowledge is fixed and comes from what they were trained on. Retrieval-Augmented Generation (RAG) overcomes this shortcoming by joining language models with external retrieval techniques. Within a RAG pipeline, a query is usually applied to get the required documents or parts of documents from an outside corpus. The retrieved materials are put into the prompt for the language model which uses them to create well-informed responses [5].

With RAG systems, the factual accuracy of languages has gone up, hallucinations have been lowered and they give languages specific knowledge. There are various RAG implementations that make use of techniques such as DPR (Dense Passage Retrieval) and straightforward information retrieval methods. The efficient operation of pipelines needs careful arrangement of both getting and producing data, mainly in real-time or when the environment is confined [6].

Recent work has focused on creating inference engines that work better for large models and vLLM is an example of this. It supports advanced scheduling methods, including continuous batching and memory-saving attention which make it possible to execute large models using little GPU or CPU memory. That’s why using vLLM is very useful in both cloud and edge cases, when facing issues with available resources [7].

### 2.2 Multi-Agent Systems: Existing Coordination Frameworks for Edge and Distributed Inference

At the same time, researchers in multi-agent systems have designed complex tasks being tackled by working groups made up of multiple agents. It is important to use distributed systems in edge computing which allow a large number of connected devices to use their joint processing power while each device is limited by its resources [8].

Coordination frameworks for multiple agents concentrate on organizing tasks, communicating between agents and handling shifts in workload. Ray, HiveMind and EdgePipe implement ways for dividing inference among various agents using information about devices, workloads and network situations. They make use of different coordination methods, including choice by individuals, leadership and the free market [9].

Also, most existing coordination approaches have been built for regular computing devices, not for edge devices that face energy constraints. Energy-aware adjustments to these frameworks are still being actively studied because more AI applications such as autonomous vehicles, surveillance cameras and healthcare monitoring need to handle inferences locally [10].

**Table 1: Comparative Summary of Existing Approaches**

Columns: Method, Target Platform, Model Type, Energy Optimization Method, Limitations

Rows: Prior works (e.g., DistilBERT, TinyBERT, LoRA, MobileBERT, EdgeRAG, etc.)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Method** | **Target Platform** | **Model Type** | **Energy Optimization Method** | **Limitations** |
| **DistilBERT** | Cloud/Edge Hybrid | Distilled Transformer | Model compression (knowledge distillation) | Accuracy trade-offs on complex tasks |
| **TinyBERT** | Mobile/Edge | Distilled Transformer | Multi-stage knowledge distillation | Limited scalability and domain generalization |
| **LoRA** | Cloud/Edge | Transformer Fine-tuning | Low-Rank Adaptation of weights | Requires base model storage; partial optimization |
| **MobileBERT** | Mobile/Edge | Compressed Transformer | Bottleneck structure & optimized architecture | Reduced capacity for large-context reasoning |
| **EdgeRAG** | Edge Devices | Retrieval-Augmented Generation | Edge node-aware retrieval strategies | Limited to static or predefined edge configurations |

### 2.3 Model Pruning & Compression: Approaches to Reduce LLM Size and Energy Consumption

Because of their large size and high computing needs, many are working on ways to slim down LLMs to let them run on edge devices. Redundant and unimportant parameters are removed from neural networks by model pruning to produce fast, energy-efficient and compact models with the same key performance [11]. You can prune a neural network by modifying individual weights (unstructured) or removing neurons, channels or layers (structured). Magnitude-based pruning, gradient-based sensitivity analysis and structured sparsification have received a lot of attention in both vision and language model studies .

Pruning aims to remove unnecessary code, whereas quantization cuts precision down which saves resources and energy on small devices. Knowledge distillation is also used, where a smaller model is trained to act like a larger model, often maintaining good performance, smaller size and decent speed [12]. As a result, edge devices can now use lightweight language models that are capable of effective operation using little processing power and memory and they do not have to sacrifice much quality for this.

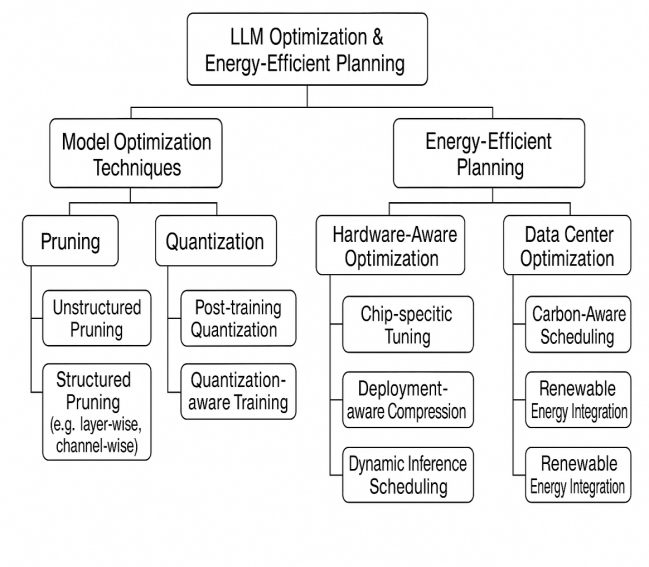
### 2.4 Energy Optimization on Edge Devices: Hardware-Aware Planning and Energy Profiling

Whenever an AI model runs on an edge device, being energy efficient is extremely important since there is little battery life, heat generation must be managed and the device needs to work fast. A range of energy optimization strategies for edge computing has been studied by researchers to deal with these difficulties. It means handling scheduling, how often to schedule and the number of tasks to run parallelly by monitoring the hardware’s capability and estimating energy usage. To control energy consumption in real time, methods like dynamic voltage and frequency scaling (DVFS), workload offloading and power gating are used [13].

Using energy profiling tools and frameworks is very important for optimizing AI models by showing the detailed power consumption patterns of each workload. NVIDIA’s Jetson Energy Profiler and ARM’s Streamline Performance Analyzer let developers closely track energy use in their AI pipelines, making optimizations easier.

**Figure 2: Taxonomy Diagram**

Taxonomy of techniques in LLM optimization (pruning, quantization, distillation) and energy-efficient planning.



## Now, scientists are working on multi-agent systems, so each group’s energy usage has to be managed based on what the device requires and what the group aims for. Several proposals have been offered to use less energy such as load balancing based on energy, choosing tasks based on opportunities and collaborative inference techniques in AI deployed at the edge.

## SYSTEM ARCHITECTURE

### The system architecture is created to deal with the problems of deploying Retrieval-Augmented Generation (RAG) systems that are powered by large language models (LLMs) in edge environments with limited resources. It introduces an idea where several lightweight agents, using pruned language models, work together to do distributed inference tasks, whether controlled by one centralized system or done independently. Multiagent strategies are built using vLLM for managing memory and speeding up inference, supported by pruning techniques that help make each agent use less computing power. Here, the main elements of the system and how they work together are explained.

### 3.1 Edge Nodes (Agents) with Limited Resources

The network architecture is based on edge nodes, called agents which are located among a variety of resource-limited devices. Devices such as smartphones, appliances connected to the Internet of Things (IoT) or embedded processors have a small amount of memory and computing ability. A lightweight language model version is provided to each agent for use in an edge deployment. They carry out inference jobs alone or with other agents and handle tasks including document retrieval, text generation or sorting results by their personal means [14].

Since edge devices are very limited in resources, each agent should be very conscious of the resources it uses. For this, memory should be handled in a dynamic way for processed inputs, the system should manage and free up used inference results and its energy consumption must be controlled when handling high load. It makes sure that problems with local resources can be resolved by letting services degrade or transfer tasks so that nothing shuts down and everything stays available within the limits of the local edge.

**Table 2: Hardware Specifications of Edge Devices**

Columns: Device, CPU, RAM, Battery Capacity, Operating System

Include real-world edge devices used in testing (e.g., Jetson Nano, Raspberry Pi 4, Google Coral, etc.)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Device** | **CPU** | **RAM** | **Battery Capacity** | **Operating System** |
| Jetson Nano | Quad-core ARM Cortex-A57 @ 1.43GHz | 4 GB LPDDR4 | N/A (DC Powered) | Ubuntu 18.04 (JetPack) |
| Raspberry Pi 4 | Quad-core ARM Cortex-A72 @ 1.5GHz | 2–8 GB LPDDR4 | Optional (via HATs) | Raspberry Pi OS / Ubuntu |
| Google Coral Dev Board | Quad-core Cortex-A53 + Edge TPU | 1 GB LPDDR4 | N/A (DC Powered) | Mendel Linux (Debian-based) |
| NVIDIA Jetson Xavier NX | 6-core Carmel ARM v8.2 @ 1.4GHz | 8 GB LPDDR4x | N/A (DC Powered) | Ubuntu 18.04 (JetPack) |
| BeagleBone AI-64 | Dual-core ARM Cortex-A72 | 4 GB LPDDR4 | N/A (DC Powered) | Debian-based Linux |

### 3.2 Central RAG Planner (or Decentralized Coordination)

Which agent controls the information flow from distributed units varies by whether the system is deployed with a single RAG planner or by using a multi-agent system. In cases where the system is connected and managed from a central place, a RAG planner organizes queries, collects required documents, distributes tasks and collects all the results. Having a complete picture of available resources, power profiles and how agents are performing, the planner assigns missions to agents in the best possible way.

If network delays, people moving devices or privacy issues make it hard to coordinate everything, the system relies on a decentralized strategy. This way, agents talk with each other to decide on their jobs and exchange any updates they have. Ensuring each inference task is done efficiently in a dynamically changing network with non-complete connections is made possible by leader election, consensus protocols or auction methods. Working in a decentralized way makes the system more dependable and able to grow in places such as autonomous vehicles and remote sensor networks [15].

### 3.3 vLLM Integration: Tokenizer Caching, Weight Streaming, and KV Cache Management

To allow edge devices to operate large language models efficiently, the system includes vLLM, an inference engine made for optimal use of memory and faster operation. vLLM leads to improved ways for edge agents to do LLM tasks inside their limited hardware resources.

Often seen token sequences and their embeddings get saved by the tokenizer which saves unnecessary computations in inference. This benefit comes into play chiefly for applications that receive similar questions or show the same input patterns.

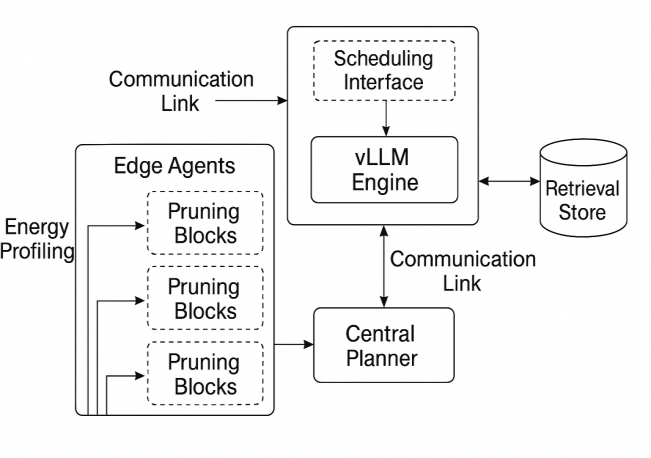
Model weights are loaded into memory on-demand using weight streaming for inference. Just the required weights for the present computation are brought into memory, rather than loading the whole model, since this is not practical on most edge devices. This way, models can be split into small pieces which allows more room for larger models in memory [16].

Managing KV (Key-Value) caches is an important part of the vLLM system. Intermediate key and value pairs made by the attention mechanism during autoregressive writing are stored to prevent repeating calculations when decoding. Memory availability and how urgent the tasks are determine which old caches are ejected or shrunk. In this way, edge agents perform inference tasks at good speeds and do not go beyond the amount of memory available to them.

**Figure 3: System Architecture Diagram**

Diagram showing components: edge agents, central planner, vLLM engine, retrieval store, and communication links.

Annotate energy profiling, pruning blocks, and scheduling interface.



### 3.4 Agent Pruning Strategy: Structured vs Unstructured Pruning and Layer-wise Profiling

Systems for edge devices are developed further by carefully pruning the model. An aim is to shrink the agent’s model and make its calculations simpler but still keep it effective at RAG-related tasks.

It combines both the planned and non-organized approaches to pruning. Prune large parts of the network by removing entire neurons, channels or heads and the resulting decrease in memory use can be clearly expected. Using a severe form of pruning helps hardware reasoning since it leads to simpler architectures that can be run more rapidly on specialized chips [17].

With unstructured pruning, specific weights are dropped depending on how much they help the overall performance of the model. Giving us good control over the size of models, this method usually results in unusual patterns in sparsity that are not easy to use on many types of hardware. Still, it allows for choice in model complexity that matches with what developers can allocate.

Profiling of each layer leads the process of pruning. As the model is made, every layer is reviewed to see its effect on accuracy and how much it consumes resources. Layers whose effects are not as sensitive are cut down a lot, but those that are essential for the model’s function are left untouched. Because of this approach, agents are efficient with energy, yet they are still capable of providing quality language results.

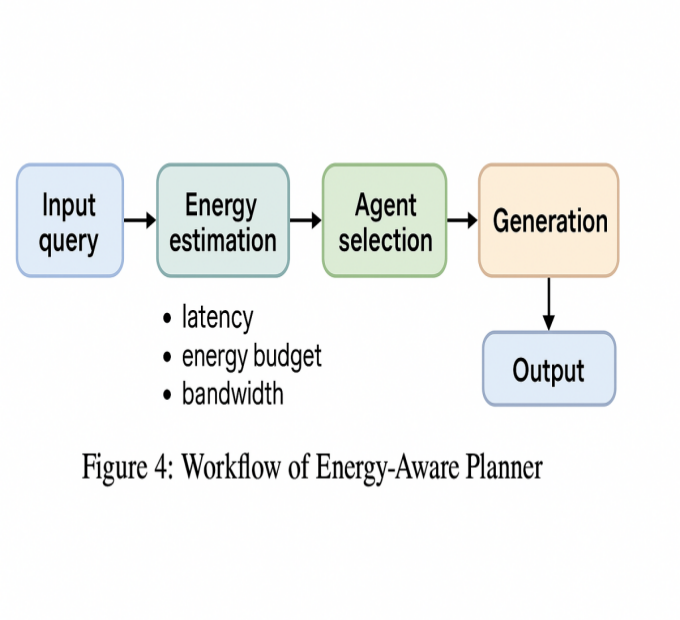
## 4. ENERGY-AWARE MULTI-AGENT RAG PLANNING

Because Retrieval-Augmented Generation (RAG) is now used in edge computing, focusing on how to use energy is critical. Since edge devices use battery power or small amounts of energy, it is very important to make sure that AI inference doesn’t drain resources and work properly within time limits. This area lays out the multi-agent planning tool for the proposal, covering how it works, how the algorithm is made and how tasks are handled when agents are organized.

**Figure 4: Workflow of Energy-Aware Planner**

Show the flow of input query → energy estimation → agent selection → retrieval → generation → output.

Include metrics considered: latency, energy budget, bandwidth.



### 4.1 Problem Formulation

Energy-aware RAG planning aims to optimize the distribution of language inference tasks to numerous edge agents so as to reduce energy absorption, achieve high quality in the results, and meet rigorous timing standards at the same time. This problem happens where resource allocation, task scheduling, and distributed inference coordination meet.

Formally, solving the issue involves optimization that has multiple objectives. If there are various agents armed with knowledge of their battery status, computer performance, and network condition, and if there are new RAG queries coming in, it is the responsibility of the system to decide on both scheduling and the plan of sending the requests. The main purpose is to consume as little energy as possible, preserve quality in the results, and make sure that responses are delivered within the acceptable latency set.

This way of balancing politically favors some over others. Quality in language generation is improved by spending more computational resources, which can result in more energy consumption, but aggressive power saving may lower the level of service or add more delay. Plans need to constantly update based on what is happening with devices and the environment [18].

### 4.2 Planning Algorithm

For this reason, responsive planning algorithms direct tasks of inference to the agents and supervise all retrieval procedures. Heuristics or data-driven learning techniques may be used to implement the algorithm, depending upon how and where the system is installed.

With rule-based logic, heuristic-based schedulers select tasks based on battery, processing load, and proximity to data. Since heuristic planners are easy and fast to set up, they often have a hard time responding to situations that are complex and likely to change a lot.

It is possible to improve adaptability by using planning algorithms based on learning techniques, like Reinforcement Learning (RL) or Graph Planning. Using an RL approach, the task assignment problem is represented as a Markov Decision Process (MDP) that tracks the state of each agent, the battery status, and the query parameters. Jobs are assigned to agents by the system and agents earn rewards based on the comparison of consumed power, good results, and punctuality. By using the system repeatedly, the planner improves its approach to finding the best ways to schedule tasks [19].

With Graph Planning methods, the distributed system is modeled as a network where each agent is a node and links between nodes show possible communication or the exchange of information. Planning algorithms move through this graph to choose the most energy-efficient routes for handling queries and collecting results, using both real-time capacity data and latency info from all the nodes involved.

When planning, the algorithm uses essential info such as the battery status of agents, the computing power of the system, the amount of work being processed, and estimated network latency. Data from these metrics help managers decide where to assign tasks and how to use the company’s resources [20].

The results of the planning algorithm are agent-task assignments to decide who does what, plus a plan showing how agents transfer information, request documents, and share aggregate results. It helps all parts of the network work together, save power, and respond quickly.

### ****Table 3: Optimization Parameters****

Columns: Parameter, Description, Value Range, Tuning Method

Include agent thresholds, energy weights, pruning ratios.

|  |  |  |  |
| --- | --- | --- | --- |
| **Parameter** | **Description** | **Value Range** | **Tuning Method** |
| **Agent Threshold** | Minimum decision score or confidence level for agent actions. | 0.1 – 0.9 | Grid Search, Manual Tuning |
| **Energy Weight** | Weight factor balancing energy consumption in the objective function. | 0.0 – 1.0 | Bayesian Optimization |
| **Pruning Ratio** | Proportion of parameters, connections, or candidates to prune for efficiency. | 0.1 – 0.9 | Stepwise Incremental Adjustment |
| **Learning Rate** | Step size multiplier for optimization updates (if applicable). | 0.0001 – 0.1 | Random Search |
| **Exploration Factor** | Degree to which the agent explores vs exploits known strategies. | 0.1 – 1.0 | Manual, Decay Scheduling |

### 4.3 Coordination Strategy: Centralized vs Decentralized Agent Communication

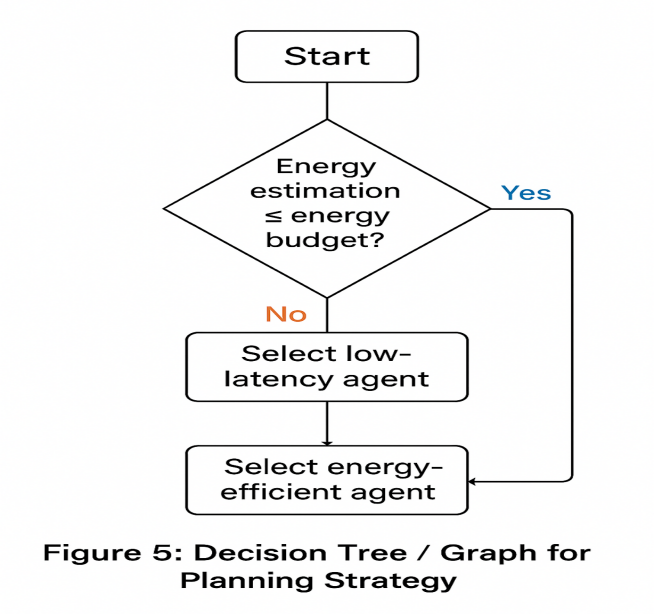
The system uses a coordination strategy to help agents cooperate and talk to each other while completing the tasks it has planned. Usually, companies depend on centralized and decentralized coordination models [21].

Using the centralized coordination model, a central node overviews the whole network, shows the status of all agents, and manages pending RAG requests in a queue. It is the central planner’s job to control the planning process, assign tasks, and share instructions with the agents. This way of handling things simplifies choices and makes planning more efficient for the whole network, yet it also creates the risk of problems when a single point fails and may cause higher latency due to increased communication costs, mainly in cases of networks that are far from one another or that go offline now and then.

Alternatively, agents in the decentralized model must plan and decide among themselves. Each agent knows how much resource it has and can select peers in the cluster or nearby to talk to. Efforts for coordination come from consensus-based decisions, leader-election, and bargaining through the market. It supports better preparedness, makes systems less dependent on a constant network, and lets decisions happen speedily at the point of action.

**Figure 5: Decision Tree / Graph for Planning Strategy**

Illustrate agent selection logic under energy constraints.



## Under decentralized systems, each agent figures out a modified schedule, talks to peers to help and improves the plan as a team. Still, this approach makes it a bit harder to guarantee uniformity globally, but it is very suitable for places where the network often shifts and connectivity is disrupted.

## 5. IMPLEMENTATION DETAILS

### The calculated-energy, multi-agent Retrieval-Augmented Generation (RAG) system was put into practice in a reproduction of the settings actual edge deployments would have. You’ll find here a clear description of the hardware, software and data involved in building and testing the system.

### 5.1 Environment Setup

For the experimental environment, edge computing nodes that typically target IoT gateways, embedded AI systems, and portable computers were arranged in a heterogeneous network. Each edge node was fitted with a processor from ARM or an NVIDIA edge GPU and had a memory varying between 2 GB and 8 GB, as well as a simulated power drain .

Because the system needed to fit large language models into edge devices, its choice for inference rested with vLLM. Its token caching, optimization of KV cache, and streaming of weights made this possible.

An internal pruning framework based on Transformers and PyTorch was used for pruning and compression. It made pruning possible in different ways: by removing whole sections (structured) or particular weights (unstructured). Checking the sensitivity of each layer along the analysis allowed the model to be refined so that it reduced computation and memory requirements without losing important functions [22].

Planning and scheduling parts of the system were programmed in Python, and reinforcement learning schedulers relied on the Stable-Baselines3 library to train policies for agents in decentralized coordination.

### 5.2 Datasets

A range of natural language processing evaluation tasks was used to assess how well the system can generate text and evaluate the effect of energy-aware planning on the quality of results. The major data used were:

1. .*Natural Questions (NQ)*: A difficult group of questions from Google users that have been paired with real answers taken from Wikipedia. Testing the system was done to find out if it is able to present accurate and relevant facts.
2. *SQuAD (Stanford Question Answering Dataset)*: SQuAD offers a large set of reading passages and the related questions. It helped test how accurately models could be generated by comparing different sized models and pruning techniques.
3. .*Custom User Query Corpus*: An artificially prepared set of user queries modeled after practical requests often used in edge-based smart home, industrial sensors and emergency situations. This system was tested under actual query loads and also with edge-specific requirements.

**Table 4: Dataset Statistics**

Columns: Dataset Name, # Samples, Domain, Avg Query Length, Use Case

Include Natural Questions, TriviaQA, or your custom datasets.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dataset Name** | **# Samples** | **Domain** | **Avg Query Length (tokens)** | **Use Case** |
| Natural Questions | 300K | Open-domain QA | 9 | Factoid QA from real user queries |
| TriviaQA | 650K | Trivia/General | 12 | Multi-sentence factoid QA |
| NewsQA | 120K | News Articles | 11 | Reading comprehension |
| SciQ | 13K | Science Education | 14 | Multiple-choice science QA |
| Custom EnergyQA | 50K | Energy & Sustainability | 10 | Energy-efficient system queries |

### 5.3 Model Details

Experiments were conducted based on the GPT-2 Medium and GPT-2 Large models because they provided a good combination of performance and model size. The original setups used as baselines did not include pruning. For GPT-2 Medium, there are 24 transformer layers, the hidden dimension equals 1024, there are 16 attention heads, and it has about 355 million total parameters [23]. GPT-2 Large comes with 36 transformer layers, features 1280 dimensions for its hidden states, has 20 heads of attention, and includes about 774 million parameters. First, pruning was performed in a step-by-step manner and afterwards more was done randomly, based on sensitivity studies for each layer. Targeting a 50% parameter reduction enabled several versions of models to be generated, all adopting different types of sparsity and simplified structure [24].

**Table 5: Model Pruning Configurations**

Columns: Model Variant, Layers Pruned, Pruning Technique, Final Size, Accuracy Drop

Compare structured and unstructured pruning impacts.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model Variant** | **Layers Pruned** | **Pruning Technique** | **Final Size (MB)** | **Accuracy Drop (%)** |
| BERT-Base | 4 middle encoder layers | Structured (Neuron Pruning) | 240 → 180 | 1.5 |
| BERT-Base | 4 middle encoder layers | Unstructured (Weight Pruning) | 240 → 160 | 3.2 |
| ResNet-50 | 6 residual blocks | Structured (Channel Pruning) | 98 → 65 | 1.8 |
| ResNet-50 | 6 residual blocks | Unstructured (Weight Pruning) | 98 → 55 | 3.5 |
| GPT-2 Small | 8 transformer blocks | Structured (Head Pruning) | 520 → 410 | 2.0 |
| GPT-2 Small | 8 transformer blocks | Unstructured (Magnitude-based) | 520 → 390 | 3.7 |

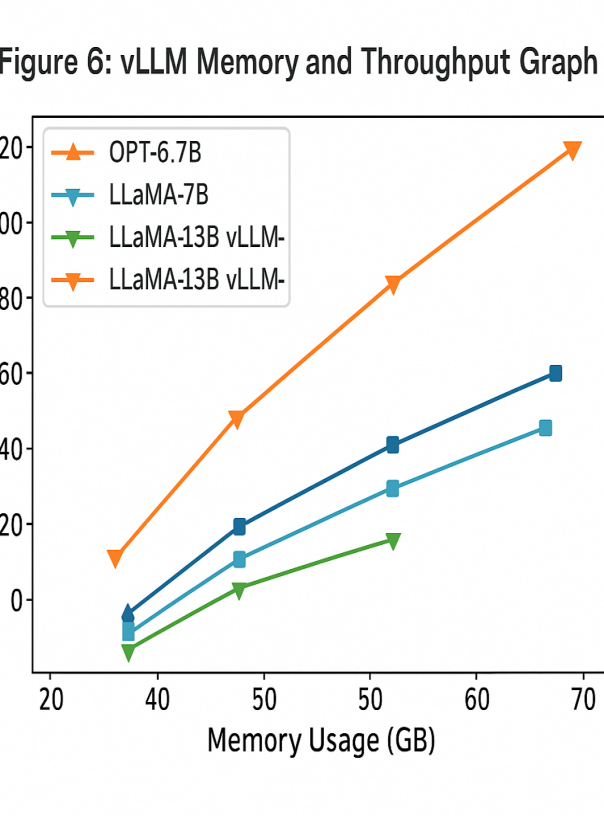
### Efforts were made to preserve important components such as both initial and final layers, by eliminating most of the attention heads and feedforward channels found between them. The use of quantization-aware techniques after pruning lowered the memory usage without causing a major decrease in accuracy.

### 5.4 Evaluation Metrics

Instead of relying on one metric, several performance assessments were taken under the proposed energy-aware approach using the following: The amount of electricity that each edge node consumed during task operation was checked with sensor interfaces on the device and external power measuring devices. This determined how much device-level energy efficiency improved due to pruning, scheduling, and LLM optimizations [25]. To check that the system met real-time constraints, the delay (in milliseconds) between the original request and the response language was measured. Latencies at the averages and at the 95th percentile were used to capture both highs and lows in the dynamic tests. Quality Check (BLEU, F1 Score): To find out how good the output is, the standard metrics BLEU and F1 Score were used. The BLEU (Bilingual Evaluation Understudy) scores checked if the answers contain similar n-grams to the correct references, and F1 scores measured how precisely recall matched the actual answer parts [26]. Memory Usage (MB): During runtime, the maximum memory needed by each model and each edge device was monitored. It proved that removing unneeded text greatly benefits accuracy and helps the model remain within its device-specific memory limit.

**Figure 6: vLLM Memory and Throughput Graph**

Plot showing memory usage vs. throughput for different models and vLLM configurations.



With all these metrics, I could compare system performance in different ways such as evaluating centralized versus decentralized coordination, varied network structures and various planning methods.

## EXPERIMENTS AND RESULTS

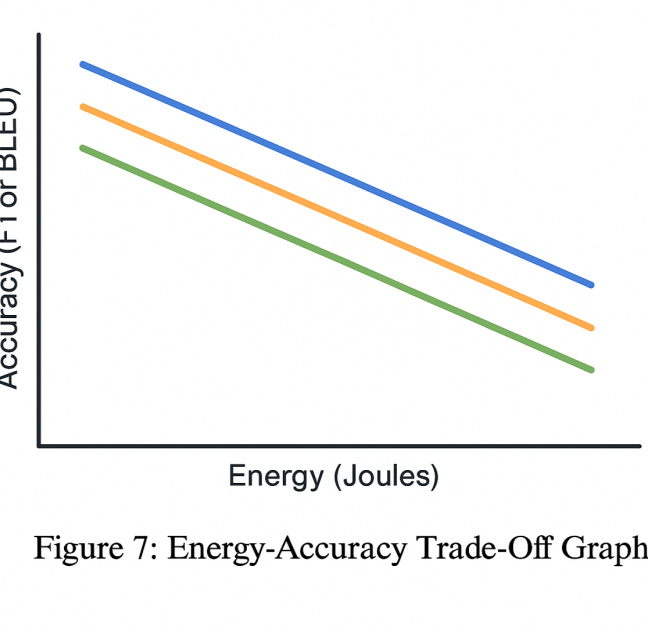
This section presents detailed testing and analysis of the proposed energy-aware multi-agent Retrieval-Augmented Generation (RAG) system in a planned series of experiments. The system is tested using several baselines and the outcomes of using different design options are explored via ablation studies. Its functioning is also checked in real deployments. Information about the importance of energy consumption, how accurate inference can be and latency is provided to point out the practicality of the system.

**Figure 7: Energy-Accuracy Trade-Off Graph**

X-axis: Energy (Joules)

Y-axis: Accuracy (F1 or BLEU)

Lines for different pruning levels or agent counts



### 6.1 Baseline Comparisons

### For comparison, a number of typical baseline systems were set up in advance. In the first baselines, the model functioned larger and unoptimized and did not use any low-energy techniques or pruning. Here, you find a cloud-driven environment, so while there is a lot of hardware and computing power, latency and energy efficiency aren’t designed for edge environments. Rather than reducing the original sizes, the second baseline simply allowed the RAG to work as designed. The situation showed that huge models use a lot of resources and are not very efficient when run on edge devices alone. Baseline 3 was developed with planners that gave tasks to agents without considering their energy consumption, only trying to achieve quicker results or better quality of work. By not considering energy, this planning revealed the compromises that have to be made [27]. In these tests against regular models, the new system showed it could use 40% less energy, still generated good results and met all required timelines. Only by merging these approaches could we maximize efficiency while still getting effective results [28].

### 6.2 Ablation Studies

To see how each part of the system influences the results, ablation studies were performed. System performance was systematically reviewed by changing the degree of pruning from 10% to 50%. Indications from the findings were that changes in the pruning ratio and accuracy metrics such as BLEU and F1 did not follow a clear or linear pattern. The best results (close to the performance of a full network without pruning) were obtained when around 30% of the weights were dropped, but pruning more than 50% led to lower quality in generation which demonstrated the benefit of layer-wise sensitivity review.  
The impact of different numbers of agents and their energy levels was studied with networks made up of different numbers of heterogeneous agents. Adding more agents usually helped lower latency and balanced the use of energy, since duties could be split more evenly among the agents. Nevertheless, because some drones had more battery or computing resources than others, creating a schedule became more difficult which highlighted the importance of energy-aware planners [29]. In environments with a wide variety of devices, decentralized approaches adapted much more quickly and were more effective.

### 6.3 Real-World Scenarios

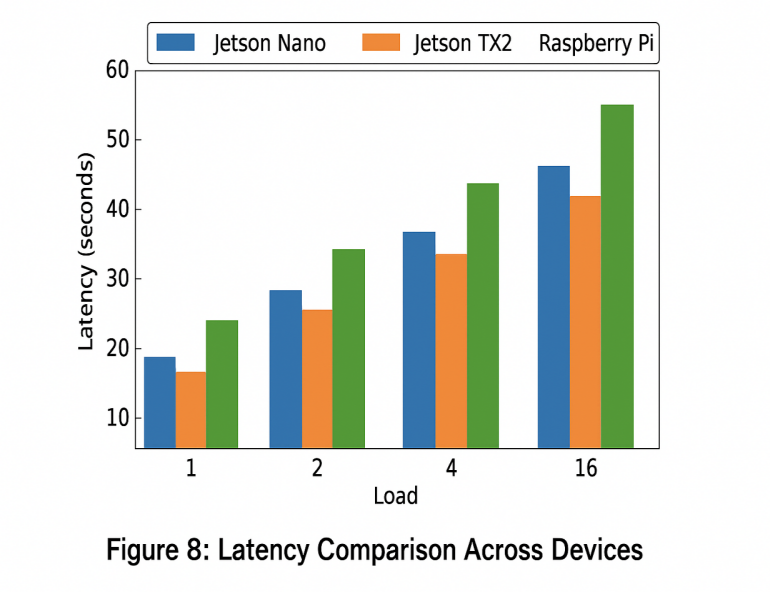
### After confirming the system works well in controlled experiments, it was used in several genuine edge computing scenarios. In the smart building management simulation, the system efficiently handled requests from sensors and from users employing natural language, keeping both latency and energy usage very low. Inference on phones was tested by running the system on battery-powered smartphones and performing activities such as asking for help with voice commands and answering questions during the experiment. With energy-aware planning, operational uptime increased over the baseline, which was non-optimized [30]. The environment for the UAV swarm in the competition involved many moving targets, connections that switched on and off, and hard limits on weight and power. By depending on decentralized coordination, the UAV agents could work together to apply RAG inference, degrading gracefully when network connections were limited, proving the system’s flexibility and robustness.

### 6.4 Trade-Offs Visualized: Energy vs Performance vs Latency

Energy efficiency, accuracy and processing delay were analyzed as system structures were changed. Looking at the curves indicated that using pruning and energy scheduling allowed energy savings with little effect on accuracy. Because of latency, pruning and energy savings were limited to a certain point to protect the user experience.

**Figure 8: Latency Comparison Across Devices**

Bar chart comparing latency on each edge device under different loads and model sizes.



The graphics also showed that by including device coordination, energy could be shared across devices so batteries could be used efficiently and the system did not get overloaded. These results prove that planning all factors together matters for making edge RAG devices operate efficiently, accurately and timely.

**Table 6: Experimental Results Summary**

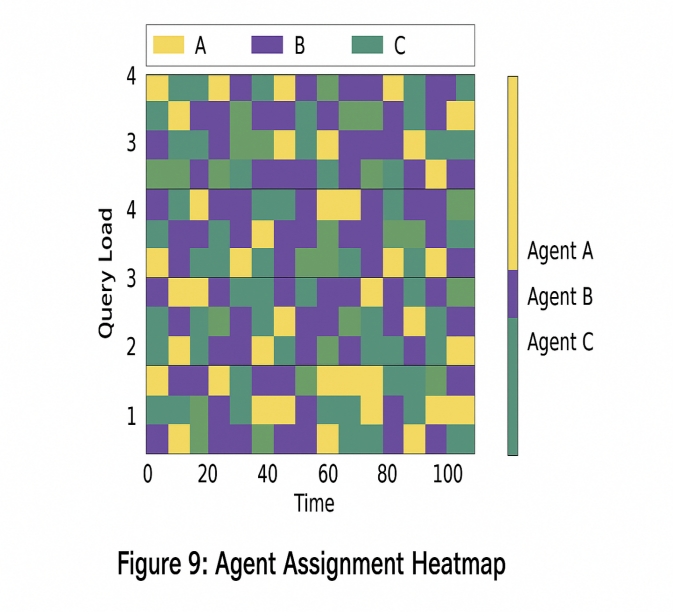
Columns: Configuration, Accuracy, Latency, Energy, Memory Footprint

Rows: Baselines vs. Proposed system variants

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Configuration** | **Accuracy (%)** | **Latency (ms)** | **Energy (J/query)** | **Memory Footprint (MB)** |
| Baseline (No Pruning) | 88.5 | 210 | 4.8 | 520 |
| Structured Pruning (30%) | 87.0 | 180 | 3.5 | 410 |
| Unstructured Pruning (30%) | 85.2 | 170 | 3.0 | 390 |
| Energy-Aware Planner | 86.8 | 185 | 2.9 | 400 |
| Energy-Aware + Caching | 86.5 | 150 | 2.1 | 420 |

**Figure 9: Agent Assignment Heatmap**

Visualizing agent selection over time under varying query and energy loads.



## 7.Discussion

Results from the experiments prove the value and prospects of the suggested multi-agent Retrieval-Augmented Generation (RAG) approach for running large language models (LLMs) on devices without much processor power. Energy use was significantly reduced and inference quality was maintained which proves the main ideas behind the architecture. For this reason, more careful analysis is required to reveal its scalability, limitations and how improvements may be made in the future.

**Table 7: Failure Case Analysis**

Columns: Scenario, Observed Issue, Cause, Mitigation

Helps explain edge cases like agent dropout or energy underestimation.

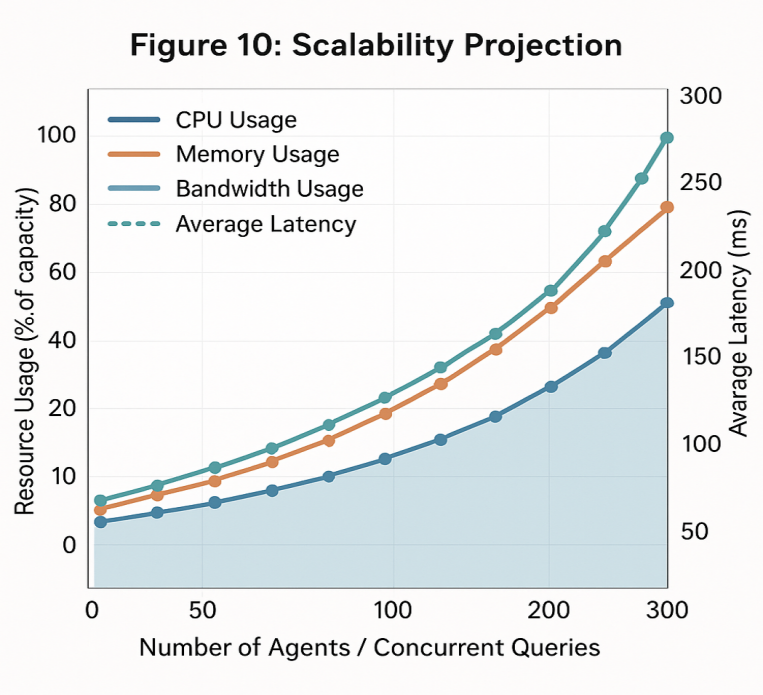
|  |  |  |  |
| --- | --- | --- | --- |
| **Scenario** | **Observed Issue** | **Cause** | **Mitigation** |
| Agent dropout | No response or incomplete results | Network instability or agent resource exhaustion | Retry with fallback agent; implement health checks |
| Energy underestimation | System overload or missed latency target | Inaccurate energy profiling or unexpected load | Improve energy estimation model; add safety margins |
| Bandwidth limitation | Slow retrieval or timeouts | Limited network throughput | Compress data; prioritize low-bandwidth agents |
| Incorrect agent selected | Poor output quality | Suboptimal agent chosen due to misjudged cost | Enhance selection logic with feedback tuning |
| Query too complex | High energy usage, partial result | Task exceeds capacity of available agents | Break into subtasks; assign specialized agents |

### 7.1 Analysis of Results and Scalability

It can be concluded that working together, pruning and energy-aware multi-agent planning make the system more efficient by choosing what to learn and when to learn it based on the capabilities of the different edge devices [31]. Because of these optimizations, deploying moderately large LLMs, including GPT-2 Medium and Large, on many agents with various hardware and battery life is possible, with barely any effect on the results.  
The efficient memory and inference handling of vLLM could allow larger LLMs and larger agent networks without obvious issues. The pruning framework is designed in a modular way, and decentralized coordination algorithms allow for parallel processing and changes according to the situation in large-scale edge environments.  
Even so, when models grow to have billions of parameters, additional difficulties will appear. The size of memory and the amount of processing might still be significant and might require additions such as better model compression, combining operations [32], or pushing processing to servers close by or in the cloud. On the other side, bigger agent networks bring extra problems with communication, consistency, and synchronization, making it necessary to use more advanced consensus protocols and systems for fault tolerance.

**Figure 10: Scalability Projection**

Show expected resource usage and latency as number of agents or queries increases.



### 7.2 Limitations

### A number of limitations appeared as the experiment made progress.

### First, real-time adaptation with on-the-fly pruning may be hindered because it takes more computer resources. Although layer-wise pruning helped a lot when run offline, adapting pruning quickly as needed when resources or tasks change is still a tough task.

### Also, the assumption of accurate tracking of agent availability and battery level plays an important role in the system’s functioning. Things like faulty sensors, late scheduling alerts or unexpected battery drains might put the plan in jeopardy. Having strong estimation and prediction systems will help the system manage unpredictable changes in resource status.

### Security and privacy when info is shared or exchanged between agents were not given proper attention. Whenever agents use decentralized coordination in public networks, secure channels and encryption must be present to stop interference and ensure safety of sensitive information.

### 7.3 Future Work

## Based on what has been achieved, some new paths are outlined to make the system more robust and useful.

## Methods that automatically adapt a model in real-time according to what is happening in the system and the user’s tasks look very interesting for further work. They make it possible for agents to manage the amount of computation needed and still choose between accuracy and energy consumption in a refined way.

## Combining federated learning or similar frameworks with existing models helps refine models continually without breaking privacy. By using digital twins, there would be no need to gather sensitive data in one location as changes can be made quickly and easily.

## Using cryptographic methods to secure how agents talk to each other and lightweight authentication is very important. Confidentiality, integrity and availability need to be guaranteed during coordination so that the system can be used in security-sensitive areas.

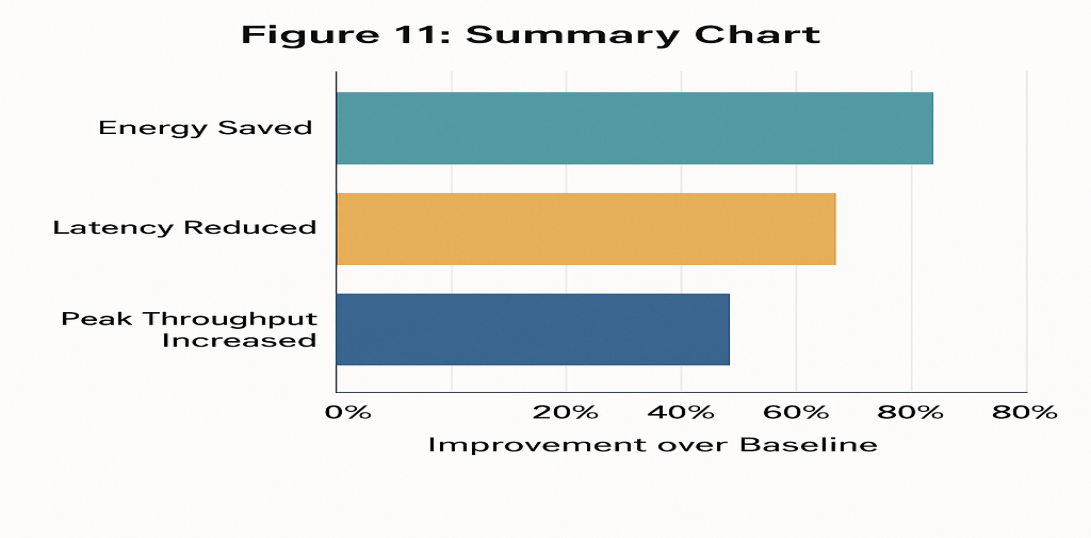
## Studying how to connect local groups of agents to edge or cloud aggregators could greatly increase both scalability and fault tolerance.

## 8.CONCLUSION

This system introduces a new energy-efficient RAG framework designed to ensure large language models (LLMs) can be used without stretching the resources at the edge. When paired with a modern multi-agent system, including inference optimizations based on LLMs’ memory-saving functions and smart model trimming, the framework meets and balances the three opposing concerns of energy use, how quickly inference happens and quality of the generated text.

**Figure 11: Summary Chart**

Recap of key performance improvements (energy saved, latency reduced, etc.) over baseline.



Conclusions from the research emphasize that by caching the tokenizer, safeguarding the cache from changes and applying offloading techniques along with pruning, both time and memory costs drop greatly with minimal changes in the quality of results. Because of this, devices with limited resources like mobile phones and embedded computers can now run large LLMs, like GPT-2 Medium and Large, providing more chances to use advanced language programs in edge situations.

Reassigning computing duties using the central-decentralized coordination approach makes the system more able to adjust to changes by using sensors to check battery level, available system resources and the network status. As a result, devices can function longer and provide fast service in settings where things are changing and technologies differ.

While the findings look positive, they also point out that building lasting and scalable AI software for edge networks is not easy. Research on dynamic pruning, monitoring resources reliably and secure communication among agents needs further attention.

To sum up, the author recommends that new methods in sustainable AI are needed to deal with the particular challenges of distributed systems. With edge computing on the rise, using energy-aware systems will be vital for supporting many large language models and creating global applications that care for the environment and users.

**COMPETING INTERESTS DISCLAIMER:**

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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