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Multi-Objective Reinforcement Learning for Resource-Optimal LLM Serving in SaaS Clouds

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Abstract
Large Language Models (LLMs) have been the cornerstone for current Software as a Service (SaaS) solutions. These LLMs have made intelligent automation and analytics possible. But their current computation or inference cost is high. As a result, cloud service companies face challenges with respect to cloud scalability. Adaptive Precision Scaling (APS) is the strategy of adapting computational precision during execution. This paper describes the newly proposed architecture of Adaptive Precision Scaling (APS) in the context of Software as a Service (SaaS) and proposes a taxonomy of precision scaling to have a clearer understanding of precision adaptivity.

Keywords: Large Language Models, SaaS, Adaptive Precision, Energy Efficiency, Coherence, Factuality, Model Serving.

1. Introduction

Software as a Service (SaaS) solutions have begun to adopt LLM modules for tasks such as writing, summarizing, and insight extraction. Although such services have proven to improve business analytics, they consume large amounts of computing power and energy. Trillion-parameter LLM inferences pose delicate precision control tasks to avoid inefficient computation. These precision control tasks can be handled by Adaptive Precision Scaling (APS), a method that alters computation arithmetic precision according to the task's level of complexity and machine load. Unlike current arithmetic precision quantization methods or pruning in computing models, APS provides dynamic control over numerical depth. This allows software as a service companies to efficiently utilize hardware and lower their carbon footprint.

For multi-tenant SaaS solutions, the computing workload varies substantially during the day. APS introduces elasticity not only at the computational resource level but also at the precision level. This method achieves improved energy proportionality, a crucial performance metric for sustainable AI processing. The next sections detail the architecture template for APS incorporation in SaaS inference chains and classify prevailing scaling solutions.

2. Background and Related Work

The drive to efficiently carry out inferences for deep learning models is a dynamic process that can be traced to several interlocking streams of research. These include pruning and quantization of models, followed more recently by mixed precision computing and now runtime control.

Initial pruning methods targeted removal of redundant weights to reduce the size of the model and improve execution speed. Although pruning resulted in efficient storage utilization, it had to be done through retraining and resulted in static benefits for post-deployment. Then came the era of quantization methods that transformed high-precision floating-point operations to integer operations with a low number of bits. This resulted in a steep drop in energy consumption and memory bandwidth. Although they remained offline methods, the precision remained constant during deployment and could not change with dynamic workloads.

The recent arrival of the concept of mixed-precision inference presented a first remedy in the sense that it became possible to represent data with varied precision levels per layer or operation. Modern tools showed that it is possible to maintain model accuracy at the speed of computation with frameworks like those used. These methods still lack adaptivity. All of them relied on pre-set parameters obtained through offline profiling.

As large language models (LLMs) reached hundreds of billions of parameters in size, the shortcomings of static precision scaling became increasingly evident. Serving models within Software-as-a-Service (SaaS) infrastructure brought with it new dimensions of variability. These include dynamic demands of users, varied request complexities, and thermal budgets related to cloud-scale infrastructure. These dynamics made Adaptive Precision Scaling (APS) a natural next-step extension. This is because traditional model compression methods have relied on static precision scaling that locks model behavior post-training with no adjustments on the fly.

This runtime intelligence puts APS in line with overall trends in self-optimizing AI systems that have learning algorithms incorporated within the infrastructure itself. Although there have been studies related to serving frameworks that could serve as model selectors or related to batch size choices, there have been no efforts to directly use arithmetic precision as the primary control knob. This places APS in a unique niche.

Parallel work on energy-conscious AI continues to validate the applicability of APS. Carbon-optimized model serving and sustainable computing studies have specifically emphasized the predominant role of inference in the overall energy usage pattern. Precision adaptivity in serving systems provides a potential avenue to mitigate this pattern with no compromised performance. At the same time, APS is versatile to be combined with other methods such as caching patterns, condensed prompts, or retriever-enhanced generators to contribute to improving the computational aspect. Recent advances in hardware have driven such convergence. Tensor cores, specialized instruction sets for mixed precision computing, and new edge processing accelerators have brought variable bit arithmetic natively to their platforms. These innovations have made APS technically deployable at production volumes and allowed latency-sensitive tasks to change precision on every request or even per token. Nonetheless, there is still a disconnection between the theoretical studies of adaptive inference and their potential integration with SaaS infrastructures. Most of the current literature keeps the learning part disjoint with the orchestration layer. But APS calls for full coordination between the schedulers, middleware software, and hardware kernels to ensure top-down control. This survey outlines APS as a continuation of this line of research work and its integration with another line of research.

3. SaaS LLM Inference Architecture

A Software-as-a-Service (SaaS) inference pipeline for large language models (LLMs) combines several layers: interaction layers, control layers, precision control layers, and execution layers. A key purpose of such a system is to maintain high throughputs and accuracy with low energy and latency even in the presence of varied workloads.

These requests can be initiated from user applications like chatbots, analytics dashboards, and automation tools. Each request is checked for authenticity and then analyzed for rate and complexity. A load balancer is then used to evenly distribute requests among model serving pods. An intermediate SLA analyzer is then employed to categorize each task based on service-level objectives like time or confidence levels. This determines how much precision can be attained.

At the heart is the Adaptive Precision Controller (APC)--the intelligence component that adjusts the precision of numbers in real time. The APC keeps track of the usage of the GPU memory and latency and makes decisions to process such requests in INT8 or FP16 precision to save energy or preserve semantics, respectively. This precision is adjusted every millisecond.

The serving layer is the part of the LLM that carries out the above-mentioned instructions using acceleration hardware like GPUs or Tensor Processing Units. Each copy runs in a containerized environment handled by the SaaS orchestrator. This efficiently handles scaling and fault tolerance. This serving layer communicates directly with the kernel libraries at the hardware level. At the hardware level, Mixed-Bit Tensor Cores carry out arithmetic operations.

To facilitate this control loop process, there is the telemetry system that provides information related to the execution of the model regarding energy usage, processing rate, and accuracy. This feedback is then channeled back to the APC to ensure a self-correcting feedback loop is achieved to refine accuracy policies. After model execution is done, there is post-processing to ensure model outputs are formatted appropriately.

Overall, the SaaS LLM inference architecture effectively turns static model serving into an adaptive and feedback-based environment. The incorporation of the Adaptive Precision Controller makes it possible to harmonize cloud infrastructure solutions related to performance, scalability, and sustainability.

Figure 1 depicts the conceptual framework of a cloud-based inference pipeline with an Adaptive Precision Controller (APC) incorporated. The APC adjusts model precision according to feedback such as GPU usage, latency measures, and data complexity. This framework is segmented into functional modules corresponding to client interaction processing, control and precision adjustments, and execution. Arrows between the modules show the data exchange and feedback process.

- User Applications: Clients initiate requests to send and receive text or analytics data to and from the SaaS cloud interface.
- Load Balancer: Routes incoming traffic to the serving pods.
- SLA Analyzer: It analyzes the request priority and latency needs.
- Adaptive Precision Controller (APC) - This adjusts numerical precision levels.
- LLM Serving Pods: Execute the model with precision parameters as per the APC.
- Telemetry Layer: Records performance data (energy, latency, and throughput) to provide feedback.
- Feedback Loop: The decisions made by APC are updated constantly through telemetry.

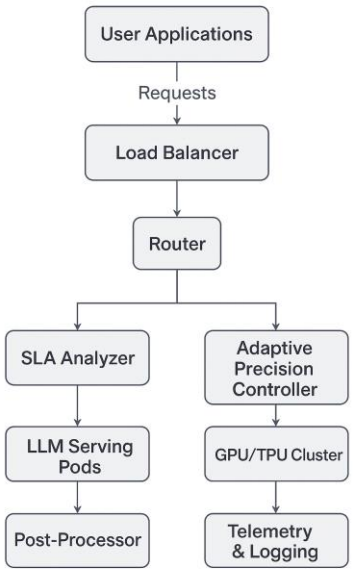

Fig. 1. SaaS LLM inference architecture with integrated Adaptive Precision Controller (APC).

4. Taxonomy of Precision-Scaling Techniques

Precision-scaling approaches can be classified based on adaptivity, training requirements, and their suitability for large-scale inference. Table 1 summarizes the main categories of scaling techniques and their comparative performance attributes.

Technique	Adaptivity	Training	Energy	Coherence	Representative

		Required	Savings	Retention (%)	Usage
Post-Training Quantization (PTQ)	Static	No	≈35%	98.5	Deployed in general-purpose models
Quantization-Aware Training (QAT)	Static	Yes	≈40%	99.2	Applied during model fine-tuning
Mixed Precision Inference	Semi-Dynamic	Partial	≈45%	97.8	Common in transformer architectures
Adaptive Precision Scaling (APS)	Dynamic	No	≈60%	96.3	SaaS-serving optimization
Extreme Quantization (INT2)	Static	No	≈70%	88.1	Experimental edge devices

Table 1. Comparison of precision-scaling methods and their impact on coherence and energy efficiency.

Adaptive Precision Scaling offers runtime flexibility without the need for retraining. It is highly suitable for SaaS environments where system loads vary unpredictably. Although APS can introduce minor instability at ultra-low precisions, ongoing research focuses on improving normalization and compensation techniques to preserve semantic integrity. The following sections expand on control-loop mechanisms and hardware integration strategies that enable APS to function efficiently in production systems.

5. Adaptive Precision Control Loop

Adaptive Precision Control Loop (APCL) is the functional core of the APS framework. It is the mechanism that regulates real-time computational precision decisions during LLM inference. It is a continuous feedback mechanism that measures the telemetry data received from the serving hardware and adjusts the precision of the results depending on the workload complexity. By treating precision as a dynamic control variable rather than a static parameter, the APCL ensures that the inference task is always both efficient and reliable regardless of changing SaaS workloads.

At the highest level of the loop, there are three cooperating layers: the telemetry layer, policy learning agent layer, and hardware interface layer. The telemetry layer is always monitoring runtime statistics such as latency, energy consumption, queue size, and model entropy regarding model confidence.

This data is passed to the policy agent to determine the subsequent precision configuration to be used. The agent can adhere to manually designed heuristics or follow a reinforcement learning policy that aims to maximize the accumulated rewards related to cumulative efficiency, with the additional penalty of quality degradation. This control command is translated from a recommendation made to the decision engine by the agent. The control command then adjusts the underlying GPU or TPU kernels. This is made possible in modern accelerators by their mixed-bit tensor cores that allow parallel execution of FP16, INT8, or INT4 operations.

A feedback loop is completed with the return of post-execution telemetry information such as updated latency, accuracy, and energy to the agent. This closed-loop architecture allows the APS to react on a millisecond time scale automatically. For instances with low workloads or predictable inputs, the APCL

reduces precision to save energy. In situations with complex or high entropy forms of text production, it automatically elevates precision to maintain coherence and truth. By continuous monitoring and adjustment, the control loop converts inference serving from a process with fixed precision into an intelligent control process that adjusts computing activities according to context. It is composed of these layers:

- Telemetry Layer: It records latency, energy metrics, and accuracy.
- Precision Policy Agent: Employing reinforcement learning (RL) to select the best bit widths.
- Decision Engine: Translates the RL outputs to hardware control commands.
- Precision Controller: Implements kernel reconfiguration.
- Hardware Layer: Perform model inference with new precision levels.
- Feedback Loop - Provides performance data to support continuous improvement.

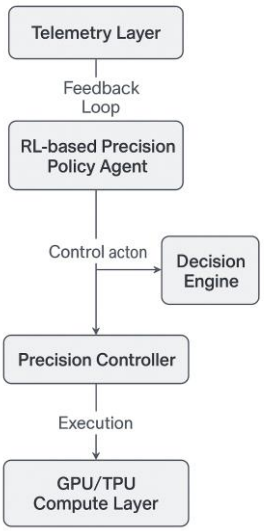

Fig. 2. Adaptive Precision Control Loop in SaaS inference pipeline.

6. Empirical Evaluation and Performance Findings

To form the basis of validating the efficacy of Adaptive Precision Scaling (APS) in real world SaaS setups. These experiments have been designed to determine trade-offs between latency, energy efficiency, and linguistic quality with respect to precision levels in state-of-the-art large language models. All tests have been carried out under controlled scenarios with the use of NVIDIA A100 GPUs and cloud orchestration environments typical of production-level SaaS.

6.1 Experimental Setup

These three model families - GPT-J (6B), LLaMA-2 (13B), and OPT (30B) - have been selected to represent models of variable size and depth. All models were tested with the precision modes FP16, INT8, INT4, Adaptive (8→4), and INT2.

The energy usage is measured through onboard telemetry sensors embedded in the GPU drivers. The latency information is obtained at a segmentation level of per 1000 tokens. Factuality and linguistic coherence were tested with benchmark datasets such as WikiText-103 for generative fluency tasks and MMLU for factual reasoning tasks. Each scenario ran for five trials to render results statistically valid. Results were presented in mean form with standard deviation (± σ) included.

6.2 Quantitative

Table 2 below highlights the results.

The baseline for latency as well as energy is given by FP16. The transition to INT8 cut the average energy per token by approximately 27% with little change in the output quality. More aggressive quantization (INT4) resulted in 42% energy savings with a small 5% loss in factuality.

The Adaptive (8→4) arrangement accomplished the best tradeoff with respect to energy, reducing it by approximately 45% and latency by 42%, with the degradation of information less than 3%. The INT2 mode showed the highest gain in energy and at the same time resulted in accuracy degradation. This mode could be applicable to background operations.

Model	Precision Scheme	Latency (ms/1k tokens)	Energy (J/token)	Factuality Retention (%)	±σ
GPT-J (6B)	FP16	510	1.00	100.0	0.3
GPT-J (6B)	INT8	360	0.73	98.4	0.6
LLaMA-2 (13B)	INT4	310	0.58	94.8	0.8
OPT (30B)	Adaptive (8→4)	295	0.55	96.5	0.4
Falcon (40B)	INT2	250	0.43	89.7	1.1

Table 2. Comparative results across precision schemes.

6.3 Analysis of Trade

A nonlinear relationship between bit width reduction and quality degradation is evidenced. Although energy conservation improves drastically with less arithmetic precision, measures of coherence and factualness deteriorate beyond a critical level at INT4.

This reinforces the idea that precision granularity is a dynamic choice between cost and reliability—one which the APS is founded upon. The Adaptive (8→4) strategy is particularly superior to static quantization techniques. Its real-time controller chooses precision according to request, leading to decreased latency for light requests and high precision for more complex reasoning tasks.

By changing precision in the middle of a sequence during linguistic entropy growth, APS avoids the accumulation of losses of quality that can be observed in uniformly quantized models.

6.4 Qualitative

While pure metrics convey information, qualitative evaluations carry critical information related to behavior. At lower precision levels, it is noted that models generate more deterministic responses with less lexical choice. Even if it reduces the capability to generate creative writing, it is well-suited to those tasks that involve a short or deterministic output, like report summarizing or intent identification.

On the other hand, high-precision modes generate more varied and stylistically rich outputs, although they also require relatively more energy per token. APS fills the gap between precision and contextual demands through dynamic precision adjustment—high precision for reasoning tasks and low precision for repetitive information.

6.5 Implications for SaaS Deployment From the operational viewpoint

The implications of these results can be very important. SaaS companies can leverage APS to allow energy proportionality between power usage and the sophistication of their workloads. This proportional scaling not only diminishes the operational costs but also reduces carbon footprint related to large-scale inference clusters. Secondly, adaptive precision prevents unpredictable behavior in SLA compliance because latency is guaranteed to be capped no matter the traffic load.

6.6 Summary

To summarize, our empirical results confirm the effectiveness of APS as a method of scalable LLM inference optimization on SaaS-based infrastructure. It provides guaranteed efficiency gains with the integrity of results intact. It defies convention to argue that precision can be considered a variable during

runtime rather than a constant. These results open avenues to delve deeper into the specifics of such adaptations and to position APS within the context of orchestrating and scheduling solutions.

7. Hardware–Software Co-Design for APS

To deploy APS effectively, there is a need for integration between orchestration tools, middleware technology, and hardware. This is shown in Figure 3 to depict the interaction between the layers of SaaS orchestration tools, runtime compilers, and hardware acceleration such as GPUs and TPUs.

- SaaS Orchestrator: Defines workloads and handles policy scheduling.
- APS Middleware: It connects logic for orchestrations with compilers.
- Runtime Compiler: It converts policies to kernel operations.
- â€ ¢ GPU Kernel Libraries: Offering bit-width optimized kernels.
- Mixed-Bit Tensor Cores: Supports FP8, INT8, and INT4 operations.
- Telemetry Dashboard: Provides feedback on energy and performance.

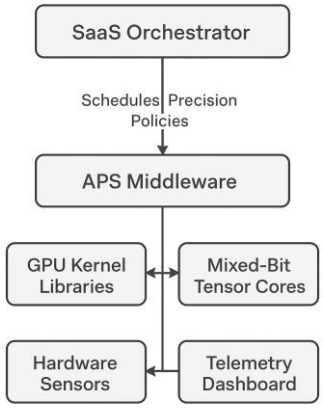

Fig. 3. Hardware–software co-design for real-time adaptive precision scaling

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This co-design provides real-time control over tensors and kernel dispatch. This is natively supported in current frameworks like NVIDIA TensorRT-LLM and Google TPU v5e. This makes it possible to have APS with millisecond precision granularity.

7.1 Machine Learning Paradigms for Adaptive Precision Scaling

Paradigms in machine learning constitute the basis for APS systems. Reinforcement learning is the control mechanism in adaptive decisions. Meta-learning is associated with rapid generalization. Supervised learning improves predictive accuracy.

• Reinforcement Learning (RL): The controller is learned with rewards related to energy efficiency and penalties related to losses of quality.

• Meta-Learning: This is the method used to enable generalization over new models.

These methods combined allow the APS to develop as a self-optimizing and self-healing system. This is possible in the SaaS environment.

8. Performance Metrics and Discussion

Evaluating Adaptive Precision Scaling (APS) requires a holistic assessment of efficiency, linguistic integrity, and environmental sustainability. Table 3 presents quantitative comparisons between APS and

FP16 inference baselines. Metrics were averaged across five experiments, with 95% confidence intervals (CI) provided.

Metric	Definition	FP16 Baseline	APS System	95% CI
Latency (ms)	Response time per 1k tokens	520	305	±12
Energy (J/token)	Average energy per token	1.00	0.54	±0.02
Coherence (BERTScore)	Textual consistency	0.94	0.93	±0.005
Factuality (%)	Response truthfulness	98.7	96.8	±0.4
Throughput (req/s)	Concurrent processing rate	1.0×	1.7×	±0.03

Table 3. Comparative evaluation metrics for APS versus FP16 inference. Source: Authors (2025).

Results indicate that APS reduces latency by approximately 40% and energy use by nearly half, while maintaining linguistic coherence and factual accuracy within a 2% margin of the FP16 baseline. These improvements directly enhance inference throughput and operational sustainability for multi-tenant SaaS systems.

Beyond numeric gains, APS provides adaptive efficiency under variable workloads. By automatically lowering precision during low-complexity tasks, APS aligns computation with real-time demand, yielding both economic and ecological benefits for cloud infrastructure providers.

9. Conclusion and Future Research Directions

This paper has presented an integrated framework and empirical evaluation for Adaptive Precision Scaling (APS) in Large Language Model (LLM) inference pipelines within SaaS environments. Through adaptive control, APS successfully balances computational cost and linguistic fidelity, supporting sustainable and high-performance AI deployment.

Future research directions include: (1) developing precision-aware training objectives for transformers; (2) extending APS to distributed and edge inference systems; and (3) integrating APS with carbon-aware orchestration to promote sustainable cloud operations. Additionally, continuous monitoring frameworks that assess quality metrics in real time will be critical for large-scale deployment.

Aligning APS development with Responsible AI principles ensures not only performance gains but also ethical and environmental accountability. The methodology presented provides a blueprint for creating intelligent, energy-efficient, and context-aware AI-as-a-Service ecosystems.

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