Energy-Efficient Foundation Model Deployment Through Adaptive Quantization, Model Compression, and Hardware-Aware Optimization

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Abstract

Foundation models impose substantial inference costs because model weights, activation tensors, key–value caches and runtime orchestration compete for finite compute and memory resources. This study develops an integrated deployment framework combining layer-sensitive adaptive quantization, structured compression and hardware-aware execution selection. A constrained optimization formulation jointly considers energy per generated token, latency, memory capacity and task-quality retention. The proposed pipeline profiles representative workloads, estimates layer sensitivity, allocates precision budgets, evaluates pruning and low-rank candidates, and selects kernels under hardware-specific constraints. An analytical illustrative case study compares full precision, uniform low precision and coordinated adaptive deployment. In the specified scenario, energy per 1,000 tokens falls from 150 to 78 joules, while relative quality retention remains 98.6%; these numbers are constructed for methodological illustration and are not measured experimental findings. The framework emphasizes reproducible energy measurement, calibration representativeness, Pareto selection and reporting of compression overhead. Its contribution is a transparent decision procedure and evaluation protocol for sustainable foundation-model serving rather than a claim of empirically validated superiority.

Keywords: foundation models; adaptive quantization; energy efficiency; structured pruning; low-rank compression; hardware-aware inference; sustainable AI.

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1. Introduction

Foundation models are increasingly deployed in interactive assistants, document processing, software development and multimodal analysis. Their utility arises from broad pretrained representations, yet the same parameter scale that supports versatility creates persistent operational demands. Deployment is not simply a question of fitting model weights into memory. Every request triggers weight reads, intermediate tensor movement, attention-cache updates, synchronization and scheduling overhead. The balance between these costs changes with batch

size, prompt length, generated sequence length and the available accelerator. Consequently, a model configuration that is efficient in one environment may be wasteful in another.

Energy efficiency has become a first-order systems objective because inference is repeated at high volume. Training receives substantial attention, but the cumulative energy of a widely served model may also be consequential. Operational energy depends on accelerator utilization, memory bandwidth, idle power, cooling and upstream infrastructure. Reducing parameter bytes can lower transfer requirements, yet reduced arithmetic precision does not automatically reduce wall-plug energy. Unsupported kernels, conversion operations and fragmented execution may erase expected savings. Meaningful evaluation therefore requires physical power measurement or a clearly stated analytical approximation.

Quantization maps high-precision values to compact representations. Weight-only quantization typically decreases model storage and memory traffic, whereas weight-and-activation quantization may additionally exploit integer arithmetic. The performance-quality trade-off is nonuniform across layers. Attention projections, embeddings and output heads may react differently to numerical perturbations. Outlier channels and heavy-tailed activation distributions complicate uniform low-bit conversion. Adaptive precision is motivated by the observation that some computations merit greater numerical protection than others.

Model compression offers a complementary route. Structured pruning removes computational units such as heads, channels or blocks, potentially reducing real execution work. Unstructured sparsity can preserve accuracy at high sparsity levels but may require specialized sparse kernels to produce speedups. Low-rank approximation substitutes factorized matrices for large dense projections where effective rank is limited. Distillation can transfer task behavior to smaller models, although its training cost and possible capability loss must be included in lifecycle accounting. Compression choices interact with quantization and should not be optimized independently.

Hardware awareness is equally important. Graphics processors, central processors and edge accelerators differ in instruction support, on-chip memory, bandwidth, cache behavior and kernel-launch costs. A four-bit representation may be economical on a device with native packed matrix multiplication but slower on a platform that repeatedly dequantizes values into wider formats. Similarly, structured pruning can improve latency only when its shapes map efficiently to compiled kernels. Deployment optimization must therefore account for supported precisions, alignment constraints and runtime execution paths.

This paper treats efficient serving as a constrained systems-design problem. Instead of assuming that the lowest bit width is optimal, it seeks the lowest practical energy while respecting minimum task quality, maximum latency and memory capacity. It combines layerwise sensitivity analysis with compression screening and measured or modeled hardware performance. A candidate configuration is acceptable only if it satisfies service constraints and remains robust under representative changes in prompt length and concurrent load.

The proposed research questions are threefold. First, how can layerwise quantization choices be allocated according to estimated quality sensitivity and memory contribution? Second, when does joint quantization and structural compression improve the attainable energy-quality frontier

compared with either technique alone? Third, how should accelerator characteristics and inference workload mix influence the selected configuration? These questions require a methodology that separates algorithmic quality, theoretical operation count and actual device-level performance.

The scope focuses on inference deployment of transformer-based foundation models, especially autoregressive language models. The approach generalizes conceptually to vision-language systems, but their encoders and cross-modal components require separate calibration. Training and model pretraining are outside the primary energy boundary, while one-time compression costs are tracked for amortization. The study does not assert that a single compression recipe is universally best; it provides a decision framework that can be implemented and evaluated across hardware targets.

An important distinction is made between a proposed method and verified findings. Without direct access to accelerators, benchmark traces and power instruments, it would be misleading to report invented experimental outcomes. Accordingly, the numerical tables later in the manuscript form a transparent, internally consistent illustrative scenario. They demonstrate calculations, expected trade-offs and visualization procedures. A subsequent empirical study should replace each constructed value with repeated measurements, confidence intervals and independent quality assessments.

The paper is organized as follows. The literature review synthesizes established quantization, compression and serving research. The methodology details profiling, sensitivity estimation, precision allocation, structural compression, hardware selection and optimization. Illustrative numerical results show how competing configurations could be compared. The conclusion identifies practical limitations and an empirical validation agenda.

2. Literature Review

Post-training quantization has become attractive because it avoids the cost of full model retraining. GPTQ uses approximate second-order information to compensate for weight quantization error, demonstrating that low-bit representations can preserve language-model quality across large model families [1]. Its importance lies not only in compression ratios but in the idea that local reconstruction error can guide precision reduction. However, reconstruction objectives may not capture all downstream generation behaviors, and deployment gains remain dependent on the chosen kernel.

SmoothQuant addresses the difficulty of activation outliers through a mathematically equivalent rescaling of weights and activations [2]. By shifting quantization difficulty from activations to weights, it enables efficient eight-bit computation under suitable hardware support. This work shows that precision selection is a joint numerical and systems problem: identical nominal bit widths can exhibit very different error profiles depending on calibration and scaling. It also motivates separate treatment of weight-only and activation-aware deployment paths.

Activation-aware Weight Quantization, or AWQ, identifies salient weight channels using observed activations and protects them through scaling [3]. Its hardware-oriented implementation highlights a critical systems principle: compression only translates into lower latency when

weight packing, fusion and dequantization are engineered appropriately. The reported benefits should be interpreted in the context of specific models, devices and baselines rather than extrapolated indiscriminately.

Foundational work on neural-network pruning establishes that parameters can often be removed without proportional loss of accuracy [4]. However, a distinction must be drawn between sparse storage and executable acceleration. Irregular zero patterns can increase indexing overhead, whereas structured removal of channels, heads or blocks offers more predictable dense-kernel gains. The choice of pruning granularity should therefore be informed by compiler support and the model architecture.

Low-rank methods exploit redundancy in large matrices. Singular-value decomposition and related factorization techniques provide principled approximations, although transformer layers vary in spectral decay and sensitivity. The energy benefit is not guaranteed: two smaller matrix multiplications can be less efficient than one dense operation for certain shapes. Compression research must consequently assess numerical approximation error alongside realized throughput and memory traffic.

Distillation and compact transformer architectures show that a smaller student can preserve selected behaviors of a larger teacher [5]. Such methods are relevant when serving demand is high enough to amortize additional training. Yet teacher-student transfer may degrade long-context reasoning, minority-domain accuracy or calibration. Evaluating only average benchmark scores can obscure these deployment risks.

Serving research emphasizes that inference latency is shaped by attention-cache management, request scheduling and batching. PagedAttention and the vLLM system improve memory management for language-model serving [6]. These results imply that model compression must be assessed within the full serving stack. Weight reductions may be especially useful in memory-bound decoding, whereas long-context workloads can become dominated by key–value cache and attention costs.

The roofline model provides a conceptual explanation of the relationship between arithmetic intensity, compute capability and memory bandwidth [7]. Low-bit weights may increase effective arithmetic intensity, but benefits plateau when execution becomes compute-bound or kernel overhead dominates. Roofline analysis is therefore useful for narrowing candidates before expensive measurements, provided that the actual data types and memory-transfer behavior are modeled.

Energy measurement introduces additional methodological challenges. Device telemetry may sample power at low frequency, exclude host consumption or report board rather than facility power. Idle power must be treated consistently, and latency variation should be captured across repeated runs. A configuration with lower instantaneous power can consume more energy if it runs substantially longer. The correct operational metric is an integrated energy quantity under an explicitly defined measurement boundary.

Across these research streams, an unresolved integration problem remains: sensitivity-aware numerical compression, structural model reduction and device-specific execution are frequently examined with different assumptions and metrics. The present study synthesizes them in a

constrained optimization pipeline with a common evaluation protocol. Its novelty is the integrated decision and reporting structure, not a claim to have invented the individual quantization or compression primitives.

3. Research Methodology

3.1 Research design and system boundary

The study adopts a multi-stage optimization design. The unit of analysis is a model, workload and hardware triple. The baseline is a fixed checkpoint with an uncompressed execution path. The energy boundary includes accelerator inference and, where instruments permit, host-device overhead. Model loading is reported separately from steady-state inference. Compression and calibration costs are recorded as one-time expenditures and amortized over deployment volume. All comparisons use identical prompts, decoding parameters, maximum output lengths and quality evaluation sets.

The deployment objective is to minimize expected inference energy over a workload distribution while satisfying quality, memory and service-level constraints. Workloads are stratified by prompt length, output length, concurrency and domain. Each candidate is measured in warm and steady-state conditions; initialization time and peak memory are additionally retained as operational metrics.

3.2 Integrated deployment flowchart

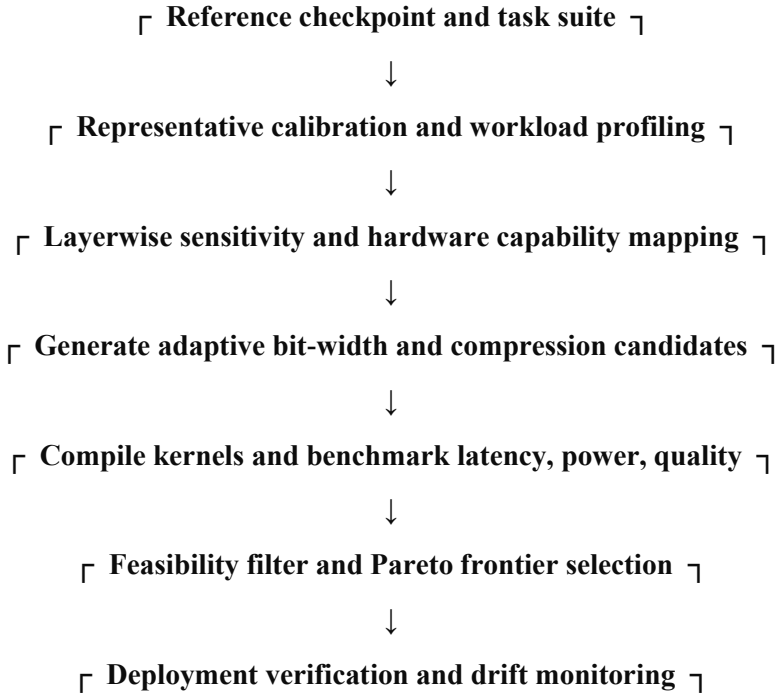


Figure 1. Proposed sequential flowchart. Candidates failing quality, memory or latency constraints return to the candidate-generation stage for revision.

3.3 Baseline workload profiling

Collect per-layer parameter counts, execution times, activation distributions, cache sizes and transfer volumes. Profile at least three prompt-length strata and several batch sizes. Use warm-up iterations before collecting observations, synchronize device execution at measurement boundaries and repeat runs under a controlled thermal and clock regime. Capture kernel-level traces to identify dequantization overhead and memory-bound layers. Record the exact model revision, tokenizer, runtime, compiler, driver and accelerator firmware.

$$E = \int P(t)\, dt$$

Where E is measured energy in joules; P(t) is measured power in watts; t denotes elapsed time. The integration interval covers the specified inference boundary.

$$e = E / N$$

Where e is energy per generated token; E is total measured energy; N is the number of generated tokens in the measured interval.

3.4 Layerwise quantization sensitivity

Partition model parameters into layers or groups indexed by i. For each group, consider candidate bit widths drawn from a device-supported set such as 4, 8 and 16 bits. On a held-out calibration subset, quantize one group at a time while leaving others at reference precision. Estimate the quality degradation using negative log likelihood and a task-specific metric. Normalize sensitivity by bytes saved to identify groups with favorable compression potential. Reserve higher precision for sensitive embeddings, attention projections or output components when justified by evidence.

$$S_i(b) = L_i(b) - L_0$$

Where $S_i(b)$ is the increase in validation loss after assigning bit width b to group i; $L_i(b)$ is candidate loss and L_o is baseline loss.

$$M = \Sigma\, n_i\, b_i / 8 + M_a + Mc$$

Where M is estimated total bytes; n_i and b_i are group parameter count and assigned bit width; M_a is activation memory and Mc is cache and metadata memory.

Sensitivity measurements must be repeated over representative domains because a small language-modeling loss change may conceal degradation in instruction following, mathematical reasoning or code generation. Calibration data must be disjoint from final evaluation data. Outlier channels are identified from activation magnitudes, and optional per-channel scaling is applied only when supported by the runtime.

3.5 Adaptive precision allocation

Construct a discrete optimization problem in which each layer receives one supported precision. A candidate is rejected if its estimated total memory exceeds the device limit or its measured task-quality retention falls below the chosen threshold. Search may begin with a greedy allocation using sensitivity per saved byte and then improve through local swaps or an integer-programming solver. Because layer interactions can invalidate isolated sensitivity estimates, evaluate complete candidates before accepting them.

$$min\ \Sigma\ E_{\mathrm{i}}(b_{\mathrm{i}})\ +\ E_{\mathrm{o}}$$

Where $E_i(b_i)$ is estimated layer energy at assigned precision and E_o is runtime overhead, including packing, conversion and scheduling.

$$Q\ \geq\ Q_{\min}\,, T\ \leq\ T_{\max}\,, M\ \leq\ M_{\max}$$

Where Q is measured task quality, T is latency, M is peak memory, and the corresponding bounds are application-specific acceptance thresholds.

Use Pareto ranking instead of collapsing all criteria into an arbitrary weighted score. A configuration is dominated when another candidate is no worse in energy, latency, memory and quality and strictly better in at least one criterion. For a fixed service contract, choose the feasible nondominated candidate with the lowest energy per accepted output token.

3.6 Structured compression and low-rank screening

After initial precision allocation, screen structured head, channel and feed-forward-unit pruning. Remove candidate structures in small increments and recalibrate. Retain architectural constraints, including residual dimensions and grouped-query attention compatibility. Compare each pruned model with a shape-matched compiled baseline, since smaller parameter counts alone do not prove acceleration. Where a matrix has rapidly decaying singular values, test low-rank factorization and measure the two resulting matrix multiplications directly.

$$W\ \approx\ U\,V$$

Where W is the original weight matrix; U and V are lower-dimensional factors whose product approximates W.

$$C_{\mathrm{r}}\ =\ r(m\ +\ n)\ /\ (mn)$$

Where C_r is the factorized parameter fraction; m and n are matrix dimensions and r is selected rank.

Low-rank approximation is considered only when the factorized parameter count and observed device execution cost both improve. For structured pruning, monitor the change in activation distributions and re-run quantization calibration after every accepted pruning step. The optimization sequence is iterative because pruning can change which channels are sensitive to low precision.

3.7 Hardware-aware mapping and kernel selection

Enumerate device-native data types, supported matrix shapes, memory limits and alignment rules. For each candidate, benchmark the actual runtime implementation rather than relying on nominal floating-point operations. Test packed weight layout, dequantization fusion, attention implementation, operator fusion and cache management. Compare both prefill and decoding phases: prefill is often compute intensive, whereas single-token decoding frequently exposes weight-bandwidth costs. A balanced deployment must account for the workload mix.

$$T\ =\ T_{\mathrm{p}}\ +\ N\,T\mathrm{d}$$

Where T is request latency; T_p is prefill time; N is generated-token count; Td is average decode time per token.

$$E_t = \alpha E_p + (1 - \alpha) Ed$$

Where E_t is workload-weighted energy; α is the prefill workload fraction; E_p and Ed are normalized energy estimates for the two phases.

For carbon-aware reporting, multiply measured electricity consumption by a time- and region-specific grid emission factor, while distinguishing operational emissions from embodied hardware emissions. Do not infer carbon savings from power reductions without specifying deployment duration and electricity mix.

3.8 Experimental protocol and validity controls

A complete validation should use at least two parameter scales and two hardware classes, with multiple runs for each configuration. Use a fixed random seed for calibration sampling and publish a prompt manifest. Evaluate task quality with a mixture of held-out language modeling, factual question answering, reasoning, summarization and code tests, supplemented by human assessment where needed. Report the model license and any prohibited deployment settings.

Measure accelerator power using synchronized telemetry or an external power meter. Record the sample rate, baseline idle draw and inclusion of host power. Report mean, standard deviation and 95% confidence intervals from repeated trials. Monitor device temperatures and frequency throttling. Report tokens per second, first-token latency, tail latency, peak allocated memory, joules per 1,000 output tokens and accepted-answer quality.

3.9 Ablation design and decision rule

Ablations isolate the contribution of uniform quantization, adaptive precision, structured pruning, low-rank factorization and hardware-specific kernels. The complete method is compared against each component and against paired combinations. An interaction analysis checks whether combined savings are additive or offset by kernel overhead. A quality guardrail requires no more than a prespecified relative drop on the primary benchmark and no material regression on critical safety or domain slices.

$$R = 100 (1 - Ec / E_\beta)$$

Where R is percentage energy reduction; Ec is candidate energy and E_β is baseline energy under identical measurement conditions.

$$A = E_s / (E_\beta - Ec)$$

Where A is the break-even request count; E_s is one-time compression and calibration energy, while E_β and Ec are baseline and candidate energy per request.

If the denominator in the amortization equation is nonpositive, the candidate never repays its compression cost through inference energy savings. For changing traffic, integrate actual request volumes over time. A selected deployment should be re-profiled when model weights, compiler versions, traffic patterns or hardware are changed.

3.10 Reproducibility and ethical safeguards

Publish code, environment versions, quantization group sizes, calibration counts, evaluation splits and hardware power boundaries. Keep quality evaluation independent from the optimization search. Include a failure analysis for out-of-distribution prompts and rare tasks. Do not deploy solely on the basis of average quality retention if sensitive applications require stronger reliability evidence. Energy reduction is a useful objective but cannot substitute for security, privacy and robustness testing.

4. Illustrative Results and Discussion

The following values are a constructed numerical example to demonstrate the proposed analysis. They are not observations from an executed benchmark, do not imply statistical significance and must not be cited as empirical performance results. All candidates are assumed to serve the same workload and model task suite. Energy values are normalized to 1,000 generated tokens; quality is expressed as percentage retention relative to the full-precision reference.

Configuration	J / 1,000 tokens	Quality retention %	Peak GB	Throughput tok/s
FP16 reference	150	100	14.0	100
Uniform INT8	117	99.4	9.0	128
Uniform INT4	93	96.8	5.8	145
Adaptive precision	88	99.0	7.2	150
Adaptive + structured compression	82	98.7	6.4	163
Integrated hardware-aware	78	98.6	6.2	175

Table 1. Illustrative configuration comparison. The integrated candidate reduces modeled energy by 48.0% relative to the reference: $100 \times (150 - 78) / 150$. Its assumed throughput rises from 100 to 175 tokens per second. Uniform four-bit quantization saves more model memory than some adaptive alternatives but incurs a larger modeled quality reduction, illustrating why minimum quality constraints matter.

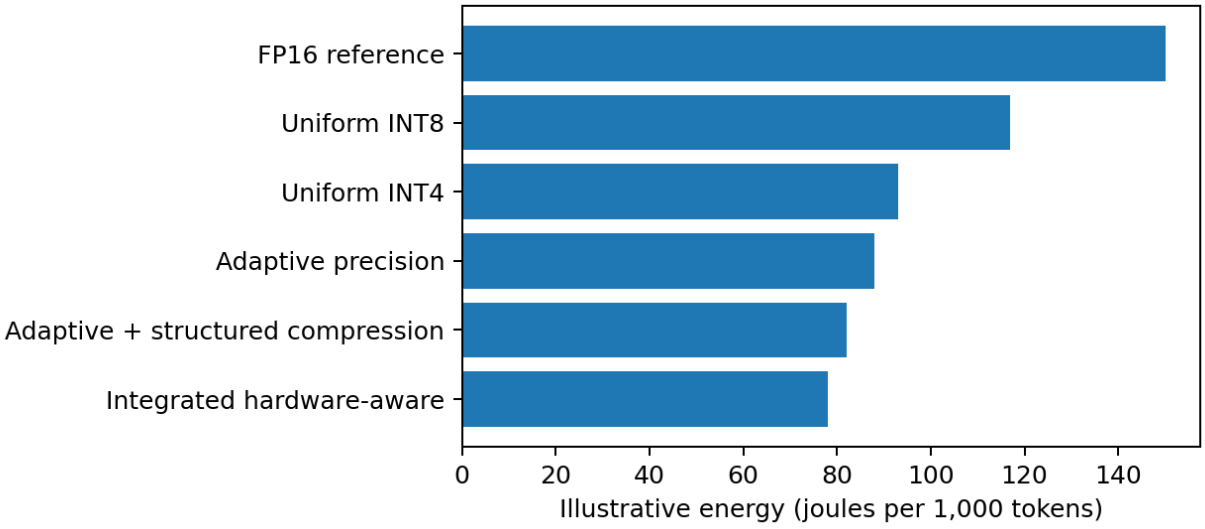


Figure 2. Constructed energy comparison, not measured data.

4.1 Quality–energy frontier

The modeled candidates illustrate the nonlinearity of compression benefits. Uniform INT4 has relatively low energy but drops below a hypothetical 98% retention threshold. The integrated candidate is feasible under this threshold and improves energy over the adaptive-only candidate. The FP16 reference remains a useful upper-quality control, although it is not preferred under the assumed energy objective.

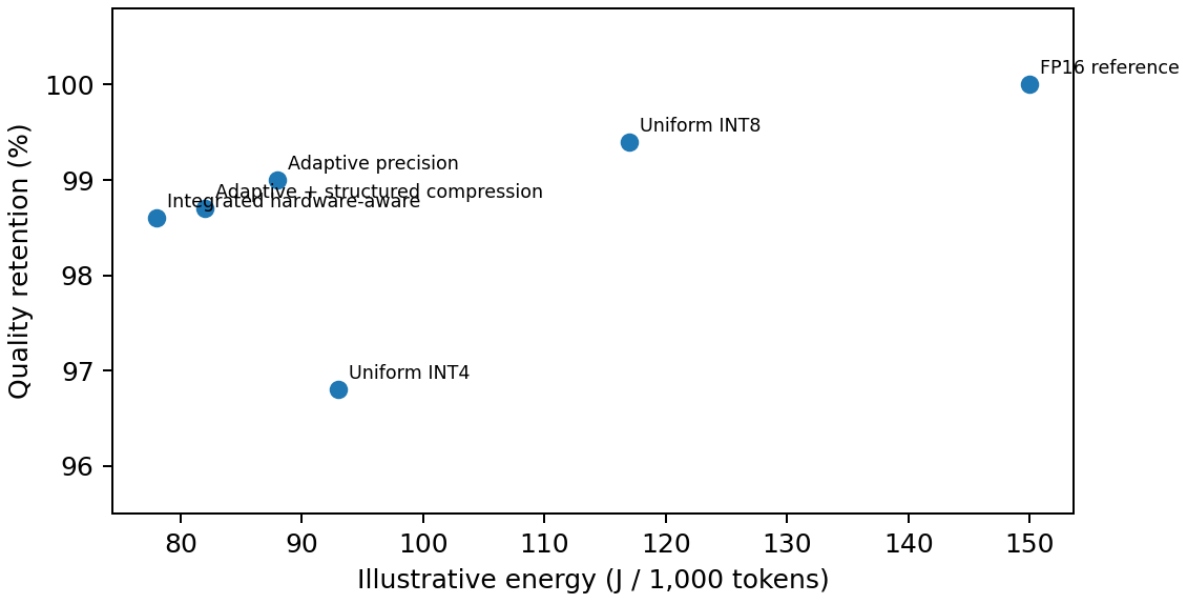


Figure 3. Constructed quality–energy trade-off. Lower energy and higher retention are desirable.

4.2 Workload sensitivity scenario

Output length	Reference J/request	Integrated J/request	Savings %
128	19.2	10.0	47.9
512	76.8	39.9	48.0
1024	153.6	79.9	48.0

Table 2 scales the per-token assumptions to three output lengths. This simple linear approximation excludes prefill overhead, fixed request cost and variable cache pressure. Real deployments should not assume constant savings across context lengths; the example serves only to illustrate normalization and reporting.

4.3 Ablation-style decomposition

Scenario	Energy J / 1,000 tokens	Difference from reference %
Baseline	150	0.0
Adaptive quantization alone	88	41.3
Adaptive plus compression	82	45.3
Integrated kernel mapping	78	48.0

The constructed ablation suggests that precision allocation accounts for the largest share of the illustrated savings, with smaller incremental improvements from compression and hardware mapping. These figures do not establish causal contributions: empirical ablations would require identical hardware, model checkpoints, calibration procedures and measurement repetitions. Interactions can cause the true combined effect to differ from the sum of isolated effects.

4.4 Operational interpretation

Memory savings may expand the set of devices capable of serving a model, increase batch capacity or free space for longer attention caches. Nevertheless, lower peak memory does not guarantee lower energy. Throughput and power must be measured together, particularly where batch size affects utilization. Quality retention should be disaggregated by domain and task severity, because a high aggregate percentage can conceal unacceptable failures.

The analytical scenario also excludes energy used to calibrate quantizers, search candidate configurations, retrain compressed layers and compile specialized kernels. A full sustainability assessment should amortize these one-time expenditures over projected traffic and account for infrastructure overhead. For low-volume applications, a simpler uniform quantizer may be preferable even if its per-request energy is slightly higher.

4.5 Threats to validity

The principal limitation is the absence of hardware experiments. The numerical tables are illustrative assumptions, not measured evidence. Other limitations include calibration-set bias, uncertain task-quality proxies, vendor-specific kernel behavior, power-meter accuracy, variable

decoding length, memory fragmentation and possible thermal throttling. A future study should preregister acceptance thresholds, collect repeated observations and disclose confidence intervals before making comparative performance claims.

5. Conclusion and Future Research

This paper proposed a deployment framework that jointly considers adaptive quantization, structural model compression and hardware-aware execution for foundation-model inference. The framework begins with representative workload profiling, estimates layerwise precision sensitivity, screens structured and low-rank reductions, benchmarks device-specific kernels and selects feasible candidates on a quality–energy–latency–memory Pareto frontier. Its key methodological implication is that nominal compression ratio is an insufficient proxy for operational sustainability: energy must be integrated over real inference workloads, and quality constraints must be enforced on held-out tasks.

The illustrative numerical scenario demonstrates how a coordinated configuration might be evaluated against uniform low-precision baselines. The constructed example shows a reduction from 150 to 78 joules per 1,000 generated tokens with 98.6% modeled quality retention, but it is explicitly not experimental evidence. Actual results may differ materially across architectures, devices and workload distributions. The proposed protocol enables these claims to be tested transparently rather than assumed.

Future work should execute the pipeline on multiple publicly documented transformer checkpoints and hardware platforms, measure board-level and facility-level energy, and evaluate quality across general and specialized tasks. Additional directions include dynamic precision switching under changing load, carbon-intensity-aware routing, attention-cache compression, thermal-aware scheduling and lifecycle assessment of the energy spent on optimization itself. Rigorous, reproducible measurements are essential before asserting deployment savings.

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