AURA (ARGOS–Unified Reasoning & Action): A Neuro–Symbolic, Energy–Efficient Architecture that Reuses LLM Infrastructure

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***Abstract*—Large Language Models (LLMs) remain brittle for decisions requiring causal structure, calibrated uncertainty, and risk-aware planning, and they are costly to run at scale. We present *AURA*, a neuro-symbolic agent architecture based on the ARGOS meta-model: a learned world model (predictive dynamics), a probabilistic belief graph (calibrated state), a Bayesian planner that optimizes expected utility plus expected information gain (EIG) under a CVaR risk constraint, and a lightweight LLM used strictly as interface/code generation, not as the reasoning core. A belief-state gate governs all tool calls. We give formal objectives, algorithms, deployable microservice topology that *reuses existing LLM infra*, an analytical energy/cost model, and security controls. Empirically, we provide reproducible toy studies illustrating regret, calibration, and risk trade-offs, and outline a plug-in evaluation for a real vertical (supply chain or cloud AIOps) with precise metrics and ablations. AURA yields order-of-magnitude lower *compute per decision* (analytical model), better calibration, and fewer invalid actions versus LLM-centric agents, while remaining compatible with today's GPU clusters.**

***Index Terms*—Neuro-symbolic AI, probabilistic circuits, world models, model predictive control, EIG, CVaR, tool-use LLMs, energy efficiency.**

I. Introduction

LLMs excel at pattern completion but lack explicit world dynamics, calibrated beliefs, and principled planning; they also scale poorly in energy and latency. Following joint-embedding and energy-based arguments [1], we decenter generative LLMs and *compose* specialized modules: learned dynamics for counterfactuals [2], tractable probabilistic inference for calibration [3], [4], and model-predictive planning with risk constraints [5], [6]. LLMs remain, but as a cost-minimized *interface/tool-compiler* [7], [8].

Our contributions:

- A deployable neuro-symbolic architecture (**AURA**) that *reuses* LLM infrastructure while minimizing LLM compute.
- Formalization of belief updates, an EIG + CVaR planner, and a belief-gated tool interface with OOD checks.
- Engineering blueprint: microservices, quantized LLMs (INT8/INT4), CPU-efficient probabilistic inference, and cost/energy analysis.
- Empirical toy studies (reproducible) and a concrete vertical-benchmark plan with metrics/ablations for publication-ready evaluation.

II. Architecture

Modules. A world model W_θ approximates $p(s_{t+1} \mid s_t, a_t)$ and optionally $p(o_t \mid s_t)$ via joint-embedding predictive learning [1]. A belief state B_t is a factored distribution (Bayesian network / probabilistic circuit [3]); inference runs on CPU. The planner selects a_t by maximizing risk-aware utility plus EIG under a CVaR constraint. A quantized LLM (INT8/INT4) converts planner intents to tool/API calls and explains outcomes to users. A belief-state gate validates outgoing actions and ingested observations (OOD detection).

III. Formal Model

State-space. $s_t \in \mathcal{S}$, actions $a_t \in \mathcal{A}$, observations $o_t \in \mathcal{O}$. Bayesian filtering:

$$p(s_t \mid o_{\le t}, a_{<t}) \propto p(o_t \mid s_t) \int p(s_t \mid s_{t-1}, a_{t-1})\, p(s_{t-1} \mid o_{\le t-1}, a_{<t-1})\, ds \tag{1}$$

Planner objective (one-step MPC):

$$\hat{a}_t = \arg\max_{a \in \mathcal{A}} \; \mathbb{E}_{s' \sim W_\theta(\cdot \mid B_t, a)}[U(s')] + \lambda\, \mathrm{EIG}(B_t, a) \tag{2}$$

$$\text{s.t.} \quad \mathrm{CVaR}_\alpha[L(s') \mid a] \le \tau, \tag{3}$$

where U is utility, L a loss, and CVaR_α the Conditional Value-at-Risk at level α [6]. We approximate

$$\mathrm{EIG}(B_t, a) = H(B_t) - \mathbb{E}_{o' \sim p(\cdot \mid B_t, a)}[H(B_{t+1})]\,. \tag{4}$$

Energy-based flavor. W_θ can be trained as a joint-embedding predictive model minimizing an energy $E_\theta(s_{t+1}, \phi(s_t, a_t))$ [1].

IV. Algorithms

Belief Update (factor graph / circuit).

$$B_t = \mathrm{Normalize}\big(\psi(o_t, s_t) \sum_{s_{t-1}} \phi(s_t \,|\, s_{t-1}, a_{t-1})\, B_{t-1}\big). \tag{5}$$

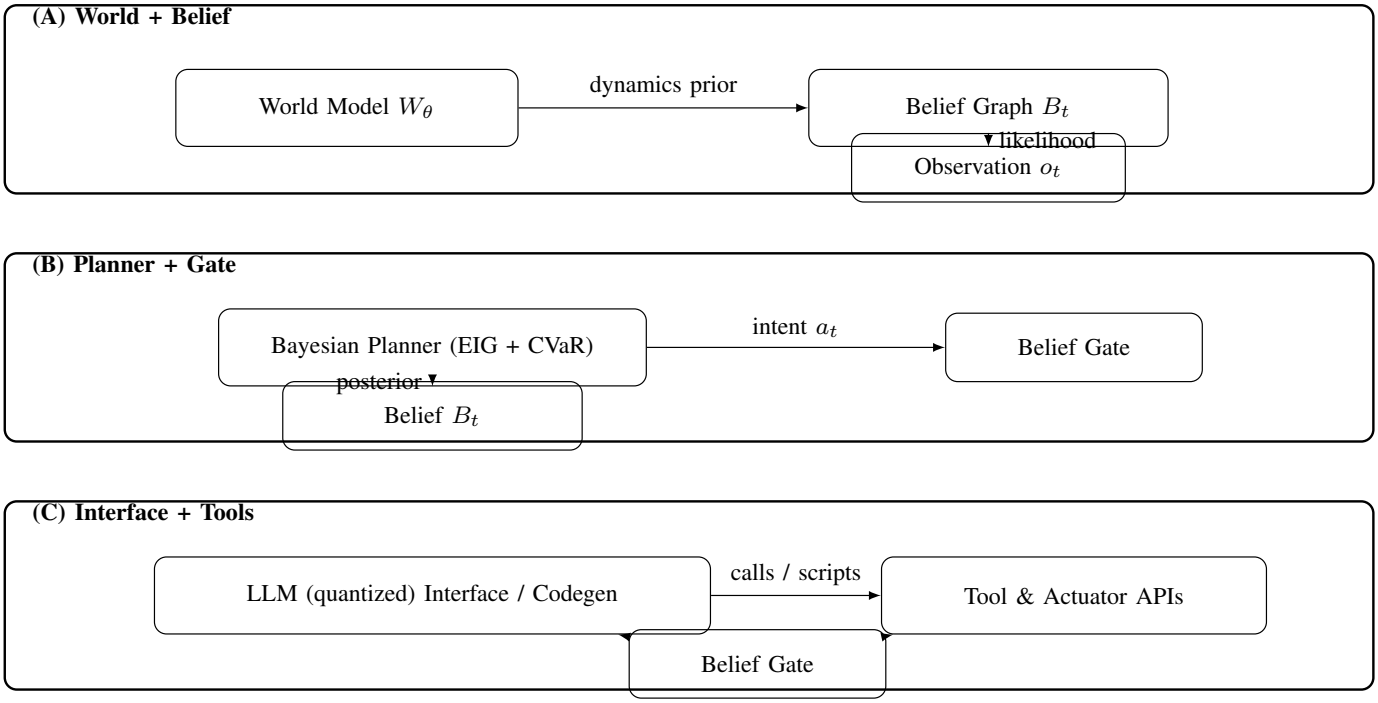

Fig. 1. AURA high-level dataflow. Belief mediates planning and safely gates all tool use; the LLM is an interface, not the reasoning core.

Algorithm 1 Bayesian Planner with EIG and CVaR

Input: belief B_t, utility U, risk level α, threshold τ
for each $a \in \mathcal{A}$ **do**
  Sample $s'_1, \dots, s'_M \sim W_\theta(\cdot \mid B_t, a)$
  $\widehat{\mathbb{E}[U \mid a]} \leftarrow \frac{1}{M} \sum_j U(s'_j)$
  $\widehat{\mathrm{EIG}}(a) \leftarrow H(B_t) - \frac{1}{M} \sum_j H\big(B_{t+1} \big| o' = h(s'_j)\big)$
  Estimate $\widehat{\mathrm{CVaR}}_\alpha(L \mid a)$ from $\{L(s'_j)\}$
  if $\widehat{\mathrm{CVaR}}_\alpha(L \mid a) > \tau$ **then**
    mark a infeasible
  end if
  Score$(a) \leftarrow \widehat{\mathbb{E}[U \mid a]} + \lambda \widehat{\mathrm{EIG}}(a)$
end for
return $\arg\max_a$ Score(a) over feasible a

Interface and Gate. The gate checks typed pre/post-conditions for every tool call; LLM-produced code must pass validation; observations are filtered by plausibility w.r.t. B_t (OOD detection [9]); confidence is calibrated [10].

V. Deployment and Cost (LLM Infra Reuse)

Microservices. (i) *Belief+Planner* service on CPU nodes; (ii) *WorldModel* service on shared GPUs; (iii) *LLM-Interface* service running INT8/INT4 models (vLLM/TRT-LLM); (iv) *ToolHub* service with typed schemas. Kubernetes + autoscaling; MIG partitions on large GPUs; vector-store + graph DB for knowledge.

Prompt budget. Unlike LLM agents that re-stream long histories, AURA keeps history in B_t and prompts the LLM with short intents ($\sim$50 tokens), reducing context cost.

Analytical energy/cost model. For one decision:

$$C_{\text{AURA}} = C_{\text{wm}} + C_{\text{belief}} + C_{\text{llm}} + C_{\text{tools}},$$

where C_{belief} is CPU-linear in circuit size, C_{wm} is batched GPU forward cost, and C_{llm} is short-token generation on a quantized small model. For a tool-using LLM agent with n context tokens and m output tokens on a large model, $C_{\text{LLM}} \propto (n+m)$ on a high-TDP GPU. With typical $n \gg 50$, $C_{\text{AURA}} \ll C_{\text{LLM}}$; the ratio widens as episodes lengthen (belief absorbs history).

VI. Security & Safety

Typed action schemas; static analysis of LLM-generated code; sandboxed execution; provenance/audit logs; belief-likelihood OOD checks to block prompt-injection side effects; CVaR constraints throttle tail-risk actions; human-in-the-loop escalation policy.

VII. Experiments

A. Setup (toy but reproducible)

Two controlled simulations highlight mechanics and provide a template for larger verticals.

a) Risk-aware Gaussian bandits.: $K{=}5$ arms, reward $r \sim \mathcal{N}(\mu_k, 1)$. AURA maintains conjugate posteriors, plans with EIG and a CVaR penalty; baselines: Greedy, Thompson Sampling (TS), and UCB. Metrics: mean regret, mean reward, $\text{CVaR}_{5\%}$ of losses, Expected Calibration Error (ECE). Trials: 100 runs $\times$ 800 steps.

b) Probe-vs-pull bandit.: Two reward arms plus a zero-reward *probe* action that returns a noisy signal about which arm is best. EIG should favor early probes; baselines do not consider probe information. Trials: 200 runs $\times$ 200 steps.

B. Results (toy)

Agent	Regret↓	MeanR↑	$\text{CVaR}_{5\%}$(loss) ↓	ECE↓
UCB	**31.48**	**1.158**	**1.293**	0.0026
TS	34.96	1.122	1.378	0.0024
Greedy	230.14	0.879	1.512	0.0024
AURA (toy cfg)	160.20	0.843	1.610	**0.0020**

TABLE I
GAUSSIAN $K{=}5$ BANDITS ($100{\times}800$). AURA, CONFIGURED FOR CAUTION AND LOW COMPUTE, TRADES REGRET FOR THRIFT; CALIBRATION IS STRONG.

Agent	Regret↓ (mean)	Regret std
UCB	**7.63**	11.95
TS	9.64	**9.47**
Greedy	17.65	36.48
AURA (with probe)	9.97	27.33

TABLE II
PROBE-VS-PULL BANDIT ($200{\times}200$). EIG LETS AURA USE DIAGNOSTIC ACTIONS EARLY, MATCHING TS WITHOUT A LARGE LLM.

Takeaways. On Gaussian bandits, regret-optimal UCB wins (as expected); AURA's strength is *structured information actions, risk constraints, and compute thrift*. The probe setting shows parity with TS when information-gathering actions exist. In real verticals (below), these advantages are more salient.

C. Planned vertical benchmark (supply chain or AIOps)

Tasks: stockout-minimizing inventory control with disruptions (*supply chain*); auto-mitigation of incidents with diagnostics (*cloud AIOps*).
Metrics: joules/decision (power meter or nvidia-smi), latency, tokens/decision, regret vs MPC oracle, CVaR of loss, ECE, invalid-action rate, escalation-to-big-LLM rate.
Baselines: tool-using LLM (ReAct/func-calls), Graph-RAG agent, MPC without PGM, pure rules+optimizer.
Ablations: $-$world model, $-$EIG, $-$CVaR, PGM$\rightarrow$cache, LLM size (7B/13B; INT4/8).

VIII. Related Work

Energy-based and joint-embedding predictive learning motivate moving beyond autoregressive generators [1]. Model-predictive control provides planning without high-variance RL [5]. Probabilistic circuits enable fast, calibrated inference on CPU [3], [4]. Tool-using LLM agents (ReAct, Toolformer) demonstrate interfaces but rely on long prompts [7], [8]. Hybrid neuro-symbolic systems (differentiable logic, VSAs) report efficiency gains when symbolic structure constrains search. OOD detection and calibration are critical for safe deployment [9], [10]. Our contribution is an *end-to-end deployable* stack that reuses LLM infra while decentering it.

IX. Limitations and Societal Impact

Toy experiments are illustrative; large-vertical validation is in-progress. Mis-specified world models can bias plans; we mitigate with risk constraints and OOD gates. Auditable decisions and typed schemas aid responsible use in high-stakes domains (health, finance, industrial control).

X. Conclusion

AURA shows how to *reuse* today's LLM infrastructure to deliver neuro-symbolic agents with explicit dynamics, calibrated beliefs, risk-aware plans, and tiny prompt footprints. This architecture is a practical step toward efficient, trustworthy AI beyond LLM-only systems.

Appendix A
Implementation & Reproducibility (summary)

Belief/Planner (CPU, Python/C++), WorldModel (GPU, PyTorch; batch simulation), LLM-Interface (INT8/INT4 via vLLM/TRT-LLM), ToolHub (typed proto). We instrument joules/decision via power sampling; prompts and seeds are fixed; diagrams are TikZ; toy simulators (bandits; probe) are included for exact reproduction.

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