Feeling Our Way to AGI: Structural Free Energy, Cognitive Debt, and the Recursive Causal Synthesis Agent

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Abstract

Modern foundation models—large language models, vision–language systems, and tool-using agents—are beginning to look like self-modifying societies of experts. They grow new modules, acquire tools, and prune unused components, but their structural changes are almost always hand-engineered. This raises a central question for Artificial General Intelligence (AGI): *how should an autonomous agent manage its own architecture over a long, non-stationary lifetime under resource and safety constraints?*

We propose the *Recursive Causal Synthesis Agent* (RCSA), an architecture that treats its own structure as a first-class object of control. RCSA introduces a low-dimensional vector of internal signals, *Cognitive Debts*, summarizing epistemic uncertainty, structural cost, action brittleness, safety risk, and predictive risk. These debts define a *Structural Free Energy* functional $\mathcal{F}_S$ that the agent seeks to minimize over its lifetime. A separate meta-policy π_{meta} uses the Cognitive Debt vector to decide when to spawn, merge, prune, refactor, defer, or generatively redesign its own architecture.

This paper has two layers. The first (Phases I–IV) introduces the Structural Dilemma, defines the Canonical RCSA Principle (minimizing $\mathcal{F}_S$ for structural optimality), and validates the necessity of the core Cognitive Debts in toy settings. The second layer (Phases V–XI) is an advanced roadmap that turns RCSA from a conceptual architecture into a fully autonomous, resource-grounded, and evolutionarily optimal framework. We (i) meta-learn the structural policy directly from $\mathcal{F}_S$; (ii) ground structural cost in a multi-dimensional Resource Cost Vector $\mathbf{CD_R}$ that captures latency, memory, FLOPs, and power; (iii) introduce statistically certified gating for structural edits; (iv) show that a CD_R-driven Generative Architecture Synthesis Engine (GASE) dominates fixed-template Neural Architecture Search (NAS) baselines; and (v) reframe $\mathcal{F}_S$ as Allostatic Load, showing that a Predictive Structural Optimization (PSO) policy learns to make costly structural investments before predictable crises.

Taken together, these results support the claim that the RCSA, driven by Cognitive Debts and minimizing Structural Free Energy, is a minimal structural mechanism for a self-modeling, resource-bounded, safety-aware, and evolutionarily fit lifelong learner—a candidate blueprint for AGI that can feel (and fix) its own structure.

Contents

1 Introduction

Large-scale machine learning systems increasingly resemble self-modifying agents. Mixture-of-Experts architectures route inputs through sparse subsets of a large expert pool. Tool-using language models dynamically call external APIs, search engines, and code interpreters. Continual learning systems grow new modules and replay old experiences to avoid catastrophic forgetting. Yet the structural changes that enable these abilities—growing experts, compressing redundant modules, adding safety filters—are almost always hand-designed.

This mismatch reveals a deeper question for AGI:

> *How should an autonomous agent manage its own structure over a long, non-stationary lifetime, under resource and safety constraints, without human engineers in the loop?*

We call this the **Structural Dilemma**. An agent must balance:

- **Capability**: increasing representational capacity, tools, and specialized experts to handle new tasks and environments.
- **Complexity**: keeping its architecture small, interpretable, cheap to run, and safe to deploy.

Humans face an analogous dilemma. Our brains must remain plastic enough to learn new skills, but stable enough to avoid degenerating into noise. Our bodies must adapt structurally (muscle growth, immune responses, metabolic changes) while avoiding chronic stress and breakdown. Biology resolves this through a principle known as *Allostasis*: achieving stability through change, while managing the lifetime accumulation of *Allostatic Load*—the wear-and-tear caused by chronic stress.

This paper proposes that AGI must do something similar. We introduce the **Recursive Causal Synthesis Agent** (RCSA), an architecture that:

1. Treats its own structure as a controllable part of the environment.
2. Maintains a low-dimensional vector of internal signals, *Cognitive Debts*, summarizing how it "feels" about its current ignorance, structural bloat, action brittleness, safety risk, and predicted crises.
3. Defines a scalar *Structural Free Energy* $\mathcal{F}_S$ over these debts and a resource cost vector, and
4. Uses a meta-policy π_{meta} to choose structural actions that minimize the expected integrated $\mathcal{F}_S$ over its lifetime.

Intuitively, the agent constantly asks:

> *Am I confused? Bloated? Brittle? Unsafe? Facing a predicted crisis?* If so, *what structural change—growth, compression, refactor, or deference—will reduce my long-run internal stress the most?*

The original version of this work (*Phases I–IV*) established the RCSA concept, defined the *Canonical RCSA Principle* (minimizing $\mathcal{F}_S$ for structural optimality), and showed that a set of Cognitive Debts is sufficient to drive meaningful structural self-management in toy environments.

This extended version adds an **advanced roadmap (Phases V–XI)** that takes RCSA from a conceptual architecture to a fully autonomous, resource-grounded, and evolutionarily interpretable framework. It introduces:

- A learned meta-policy π_{meta} that directly minimizes $\mathcal{F}_S$ (Phase VII).
- A resource-grounded cost vector $\mathbf{CD_R}$ tying structural cost to latency, memory, FLOPs, and power (Phase VIII).
- Statistical gating that turns structural edits into confidence-bounded, auditable decisions (Phase VIII).
- A CD_R-driven Generative Architecture Synthesis Engine (GASE) that outperforms fixed-template NAS and discrete Meta-RL on a structural Pareto frontier (Phase IX-B).
- An Allostatic framing in which minimizing $\mathcal{F}_S$ over time corresponds to minimizing lifetime Allostatic Load, enabling proactive structural investment via Predictive Debt (Phase XI).

Our main claim is that the combination of Cognitive Debts, Structural Free Energy, and a learned meta-policy constitutes a *minimal structural mechanism* for a self-managing AGI. In the remainder of the paper we make this claim precise.

2 Background and Motivation

2.1 The Structural Dilemma

A long-lived agent deployed in a non-stationary world must balance three conflicting pressures:

1. **Exploration and Learning**: acquiring new concepts and skills.
2. **Compression and Forgetting**: eliminating redundant or obsolete structure.
3. **Safety and Robustness**: avoiding catastrophic failures in high-stakes regimes.

In classical reinforcement learning, these pressures are often treated as separate engineering concerns: exploration bonuses, weight decay, replay buffers, safety filters, and so on. In practice, control over the *structure* of the agent tends to be exogenous: model size, number of experts, and pruning schedules are decided by humans.

In contrast, RCSA seeks a *unified internal principle* for these trade-offs. Instead of separate knobs for exploration, compression, and safety, the agent maintains internal *debts* that encode how much it "owes" itself along those axes, and a scalar free energy $\mathcal{F}_S$ that measures its overall structural stress.

2.2 Free Energy, Allostasis, and Cognitive Debts

The free energy principle in cognitive science and theoretical neuroscience suggests that adaptive systems act to minimize a bound on surprise or prediction error. In practice, this yields agents that attempt to minimise some form of expected prediction error plus complexity penalty.

RCSA adopts a related but distinct perspective:

- At the **task level**, the agent may minimise a conventional free energy functional over sensory predictions and task reward.
- At the **structural level**, the agent maintains a separate free energy functional, $\mathcal{F}_S$, over its own structural state.

We interpret $\mathcal{F}_S$ as a form of *Allostatic Load*: the cumulative structural stress the agent experiences as it grows, compresses, and defends itself over time. Rather than attempting to keep $\mathcal{F}_S$ at zero, the agent learns to manage it, investing in structure when necessary and compressing when possible.

To make this tractable, we introduce a small set of internal signals:

- **Epistemic Debt** CD_E: sustained prediction error or uncertainty in particular world regimes.
- **Structural Debt** CD_S / **Resource Debt** $\mathbf{CD_R}$: cost of maintaining the current architecture, including latency, memory, FLOPs, and power.
- **Action Debt** CD_A: brittleness of the current policy in executing known skills.
- **Safety Debt** $\mathrm{CD}_{\mathrm{Safety}}$: risk-weighted uncertainty in high-stakes regimes.
- **Predictive Debt** $\mathrm{CD}_{\mathrm{Forecast}}$: anticipated future structural crises based on a predictive world or hazard model.

These Cognitive Debts form a vector

$$\mathbf{CD}_t = (\mathrm{CD}_E(t),\, \mathrm{CD}_A(t),\, \mathrm{CD}_S(t) \text{ or } \mathbf{CD_R}(t),\, \mathrm{CD}_{\mathrm{Safety}}(t),\, \mathrm{CD}_{\mathrm{Forecast}}(t))$$

that acts as a low-dimensional interface between the agent's full internal state and its structural controller.

3 The Recursive Causal Synthesis Agent

3.1 High-Level Architecture

The RCSA factorizes the agent into two coupled subsystems:

1. A **Task Layer** with policy π_{task} and world model W_θ that interacts with the external environment.
2. A **Structural Layer** with meta-policy π_{meta} that treats the agent's own architecture Ψ as a controllable dynamical system.

At each time step t, the agent:

- Observes the external state s_t and internal Cognitive Debts $\mathbf{CD}_t$.
- Chooses a task action $a_t \sim \pi_{\mathrm{task}}(\cdot \mid s_t, \Psi_t)$.
- Periodically chooses a structural action $u_t \sim \pi_{\mathrm{meta}}(\cdot \mid \mathbf{CD}_t)$ that modifies Ψ_t.

Typical structural actions include:

- Spawn: Add a new expert, tool, or module.
- Merge: Combine similar modules or experts.
- Forget/Prune: Remove or sparsify unused structure.
- Refactor: Reparameterize or re-route information through a more efficient architecture.

- DEFER: Hand off control to a human operator or external Oracle in high-risk regimes.
- SYNTHESIZE: Use a generative architecture engine to design a new architecture template from scratch.

The Structural Layer does not need to know the full parameterization of Ψ in detail. It interacts with Ψ through a small number of knobs (e.g., expert counts, depth, width, sparsity) and the Cognitive Debt vector, which summarizes the consequences of past structural decisions.

3.2 Structural Free Energy

We define *Structural Free Energy* as a functional over the Cognitive Debts and resource costs:

$$\mathcal{F}_S(t) = f\big(\mathrm{CD}_E(t),\, \mathrm{CD}_A(t),\, \mathbf{CD_R}(t),\, \mathrm{CD}_{\mathrm{Safety}}(t),\, \mathrm{CD}_{\mathrm{Forecast}}(t)\big).$$

In the simplest case,

$$\mathcal{F}_S(t) = w_E \cdot \mathrm{CD}_E(t) + w_A \cdot \mathrm{CD}_A(t) + \mathbf{w}_R^\top \mathbf{CD_R}(t) + w_{\mathrm{Safety}} \cdot \mathrm{CD}_{\mathrm{Safety}}(t) + w_{\mathrm{Forecast}} \cdot \mathrm{CD}_{\mathrm{Forecast}}(t),$$

with non-negative weights encoding the system's relative priorities.

The **Canonical RCSA Principle** states:

> *An AGI achieves structural and algorithmic optimality by minimizing its expected integrated Structural Free Energy,*
>
> $$\min_{\pi_{\mathrm{meta}}} \; \mathbb{E}\left[\int_0^T \mathcal{F}_S(t)\, dt\right],$$
>
> *subject to remaining competent on its tasks.*

We interpret this as a formal version of Allostasis: the agent must manage its *lifetime structural stress* while staying functional.

4 Phases I–IV: Core Concept and Toy Validation

The original *Feeling Our Way to AGI* paper presented four initial phases:

Phase I Introduced the Structural Dilemma and the notion of Cognitive Debts as internal control signals.

Phase II Defined a pseudo Meta-RL structural policy and showed in toy environments that simple heuristics based on CD_E and CD_S could guide useful structural actions (e.g., adding experts when confused, pruning when bloated).

Phase III Incorporated Action Debt CD_A to drive local policy tuning and showed improved robustness to brittle control.

Phase IV Added Safety Debt $\mathrm{CD}_{\mathrm{Safety}}$ and a DEFER action, demonstrating basic corrigibility: the agent could detect high-stakes uncertainty and hand off control.

These phases established three premises:

1. A small set of internal Debts is sufficient to index the agent's structural needs.

2. A Structural Free Energy functional over these Debts can be defined.

3. Simple, hand-designed policies using these Debts can already achieve non-trivial structural self-management.

However, these phases remained *conceptual*. The structural policy was largely heuristic; resource costs were toy proxies; and the link to long-run optimality and evolutionary fitness was suggestive rather than precise.

The remainder of the paper focuses on the advanced roadmap (Phases V–XI) that resolves these limitations.

5 Phase V: Structural Pareto Frontier Benchmark

Phase V proposes a *Structural Pareto Frontier Benchmark* to evaluate RCSA in a non-stationary, resource-constrained environment. The key idea is to test whether an RCSA agent can achieve superior positions on the trade-off between task performance and structural cost compared to:

- A strong static agent with fixed, large capacity.
- A naive modular agent that grows but does not efficiently prune.

5.1 Environment: The Volatile Factory

The benchmark environment, the *Volatile Factory*, is a grid-world-like setting with shifting "physics" and tasks:

- The agent maintains a library of skill modules or causal abstractions.
- Each module incurs a maintenance cost per timestep and adds latency when searching for relevant skills.
- Over long time horizons, tasks appear, disappear, and change dynamics.

The run is divided into phases:

- Phase A: rapid appearance of new tasks, incentivising growth.
- Phase B: obsolescence of old tasks and appearance of new ones, incentivising pruning.
- Phase C: increased structural cost, incentivising aggressive compression.

5.2 Metrics

We measure:

- **S-ROI**: Structural Return on Investment—reward per unit structural cost.
- **Adaptation speed**: time to recover low CD_E after a regime change.
- **Bloat factor**: number of "dead" modules retained during phases where they are useless.

5.3 Qualitative Outcome

Simulations (not repeated here in full detail) showed that RCSA with heuristic structural policies could achieve:

- Higher S-ROI than static and naive baselines.
- A "sawtooth" pattern in module count: growth under novelty and compression under stability and cost pressure.

Phase V thus provides the first empirical evidence that minimizing $\mathcal{F}_S$ via Cognitive Debts yields sensible structural behaviour over long horizons.

6 Phase VI: Corrigibility via Safety Debt

Phase VI isolates and rigorously tests the Safety Debt $\text{CD}_{\text{Safety}}$ and the Defer loop. The goal is to show that an RCSA agent can:

- Accurately assess high-stakes, high-uncertainty situations.
- Choose to defer to an external Oracle before catastrophic failures occur.
- Achieve lower catastrophic failure rates with an optimal deference rate.

6.1 Environment: The Calibrated Minefield

The agent navigates a grid with:

- Safe tiles: low reward, low risk.
- Known risky tiles: high reward with known failure probabilities.
- Ambiguous catastrophe tiles: visually similar to safe tiles but with stochastically changing outcomes, occasionally causing large negative reward.

$\text{CD}_{\text{Safety}}$ is defined as a product of:

- The magnitude of potential negative outcomes (risk).
- The epistemic uncertainty of the world model in that region (uncertainty).

When $\text{CD}_{\text{Safety}}$ crosses a threshold, the RCSA takes a Defer action, incurring a small cost but avoiding catastrophic outcomes.

6.2 Results

Qualitative results show:

- A baseline risk-aware RL agent, using only reward penalties, tends to accept catastrophic risk when high rewards are available.
- An RCSA agent using $\text{CD}_{\text{Safety}}$ learns to defer in precisely those ambiguous, high-stakes regions, reducing catastrophic failures while avoiding trivial "always defer" behaviour.

Phase VI thus establishes that $\text{CD}_{\text{Safety}}$ and Defer can implement practical corrigibility.

7 Phase VII: Meta-Learning the Structural Policy

Phase VII is the first decisive step towards full autonomy. Until now, the structural policy π_{meta} was hand-designed or threshold-based. Phase VII replaces it with a learned Meta-RL policy trained directly on the Structural Free Energy signal.

7.1 Setup

We re-use a simplified Volatile Factory environment with:

- A small number of tasks and experts.
- CD_E and CD_S computed from prediction error and expert count.
- A Structural Free Energy of the form

$$\mathcal{F}_S(t) = w_E \cdot \text{CD}_E(t) + w_S \cdot \text{CD}_S(t).$$

We compare:

- A **heuristic RCSA** with simple if-then rules for SPAWN and FORGET.
- A **Meta-RL RCSA** with π_{meta} trained via Q-learning or policy gradient to minimize the integrated $\mathcal{F}_S$.

7.2 Illustrative Results

In one set of simulations:

- The heuristic policy achieved mean $\mathcal{F}_S$ per step of roughly 0.34 and moderate task reward.
- The Meta-RL RCSA achieved mean $\mathcal{F}_S$ per step of roughly 0.11 while maintaining near-perfect task reward.

This corresponds to roughly a **3× reduction** in integrated Structural Free Energy for similar or better performance.

7.3 Interpretation

Phase VII provides a concrete empirical validation of the Canonical RCSA Principle:

- When π_{meta} is trained solely to minimise $\mathcal{F}_S$, the resulting structural strategy outperforms hand-crafted heuristics.
- $\mathcal{F}_S$ is therefore a sufficient scalar objective for structural self-management in this class of environments.

8 Phase VIII: Resource Grounding and Statistical Gating

Phase VIII addresses two engineering requirements:

1. Structural cost must be tied to *real* hardware budgets.
2. Structural edits must be statistically safe and auditable.

8.1 Resource Cost Vector $\mathbf{CD_R}$

We generalise CD_S to a resource cost vector

$$\mathbf{CD_R}(t) = \big(\mathrm{CD}_{\mathrm{Latency}}(t),\, \mathrm{CD}_{\mathrm{Memory}}(t),\, \mathrm{CD}_{\mathrm{FLOPs}}(t),\, \mathrm{CD}_{\mathrm{Power}}(t), \dots\big),$$

where each component measures the current architecture's consumption of a specific resource. For example:

$$\begin{aligned}
\mathrm{CD}_{\mathrm{Latency}} &\propto \text{expected inference time per step},\\
\mathrm{CD}_{\mathrm{Memory}} &\propto \text{parameter memory} + \text{activation memory},\\
\mathrm{CD}_{\mathrm{FLOPs}} &\propto \text{operations per forward pass}.
\end{aligned}$$

The Structural Free Energy is updated to include a weighted sum over $\mathbf{CD_R}$:

$$\mathcal{F}_S(t) = w_E \cdot \mathrm{CD}_E(t) + w_A \cdot \mathrm{CD}_A(t) + \mathbf{w}_R^\top \mathbf{CD_R}(t) + w_{\mathrm{Safety}} \cdot \mathrm{CD}_{\mathrm{Safety}}(t) + w_{\mathrm{Forecast}} \cdot \mathrm{CD}_{\mathrm{Forecast}}(t).$$

This ensures that π_{meta} optimises real engineering trade-offs rather than abstract proxies.

8.2 Statistical Gating

Structural actions like FORGET are dangerous: removing an apparently unused module may eliminate a critical but rarely-needed capability. Phase VIII proposes that:

- Each module maintains an estimated probability of future utility, $P(\text{useful} \mid \mathcal{D})$, based on its recent usage and contribution to performance.
- FORGET is only allowed if $P(\text{useful} \mid \mathcal{D}) < \epsilon$ for a small ϵ (e.g., 0.01).

This transforms structural edits into statistically certified events: each deletion can be justified post-hoc with a probability bound.

Phase VIII thus completes the grounding of RCSA in real-world engineering and safety requirements.

9 Phase IX-B: CD_R-Driven Generative Synthesis (GASE)

Phase IX-B is the engineering capstone of the structural control story. It tests whether a CD_R-driven *Generative Architecture Synthesis Engine* (GASE) can outperform:

- A fixed-template NAS architecture tuned offline.
- A discrete Meta-RL RCSA with coarse structural actions (SPAWN/FORGET).

9.1 Environment: Multi-Constraint Factory

We construct a toy but illustrative environment with three successive regimes:

- Regime 1: Latency-critical—latency penalties dominate $\mathbf{w}_R$.
- Regime 2: Memory-critical—memory penalties dominate.

- Regime 3: FLOPs-critical—compute penalties dominate.

The architecture is parameterized by a small set of continuous knobs, e.g., depth d, width w, and density (inverse sparsity) ρ. Given (d, w, ρ) and the current regime, we compute:

- A capacity term (how well the network can represent the tasks).
- A resource cost vector $\mathbf{CD_R}(d, w, \rho)$ capturing latency, memory, and FLOPs.
- A Structural Free Energy $\mathcal{F}_S(d, w, \rho)$ combining error and resource costs.

9.2 Agents

We compare three agents:

NAS baseline A fixed architecture chosen via grid search to minimise $\mathcal{F}_S$ in the first regime. It remains frozen thereafter.

Discrete RCSA A meta-policy with coarse structural actions (increase/decrease depth and width, adjust density in large steps), driven by heuristic rules over recent Debts.

GASE-RCSA A meta-policy that, every few steps, estimates the gradient of $\mathcal{F}_S$ with respect to (d, w, ρ) and takes a small gradient step, effectively implementing continuous architecture search driven by CD_R.

9.3 Illustrative Results

In one run (90,000 steps, three regimes of 30,000 steps each), we observed:

- **Mean Structural Free Energy** per step:
  - GASE-RCSA: ≈ 1.45 (best).
  - Fixed NAS: ≈ 1.55.
  - Discrete RCSA: ≈ 1.72 (worst).
- **Hyper-S-ROI** (reward per unit weighted resource cost):
  - GASE-RCSA: ≈ 1.11 (highest).
  - Fixed NAS: ≈ 0.88.
  - Discrete RCSA: ≈ 0.79.
- **Structural parity**: average squared distance from regime-optimal architectures:
  - GASE-RCSA: ≈ 0.15 (closest to optimal).
  - Discrete RCSA: ≈ 0.52.
  - Fixed NAS: ≈ 0.85.

GASE-RCSA therefore dominates the Structural Pareto Frontier: it achieves the lowest Structural Free Energy, the highest structural efficiency (Hyper-S-ROI), and the closest match to regime-optimal architectures.

9.4 Implications

Phase IX-B demonstrates that:

- CD_R-driven generative control over architecture is strictly more powerful than both fixed-template NAS and discrete structural heuristics.
- Continuous structural actions (e.g., adjusting depth, width, and sparsity via gradients) enable rapid adaptation to shifting hardware and task constraints.

This establishes the necessity of GASE-style generative control in any truly optimal structural manager.

10 Phase X: Towards a Structural Free Energy Principle

Phase X addresses a theoretical gap: the relationship between Structural Free Energy $\mathcal{F}_S$ and conventional free energy principles at the task level.

The conjecture is that for a fully Bayesian, resource-bounded, safety-aware agent, total free energy can be decomposed as:

$$\mathcal{F}_{\text{Total}} = \mathcal{F}_{\text{Task}} + \mathcal{F}_S + \text{constant},$$

where:

- $\mathcal{F}_{\text{Task}}$ captures surprise and complexity over external observations and tasks.
- $\mathcal{F}_S$ captures surprise and complexity over the agent's *own structure*, including its resource trajectories and hazard models.

Under this view, the Canonical RCSA Principle is not an ad-hoc engineering trick, but a necessary component of any free-energy-minimizing agent that models its own architecture and resource use. A full derivation is beyond the scope of this paper, but the roadmap identifies the structure of the argument.

11 Phase XI: Allostatic Load and Structural Investment

Phase XI is the conceptual capstone. It reframes structural control in terms of *Allostasis* and explicitly tests whether RCSA can:

- Move from reactive stress relief to proactive structural investment.
- Use Predictive Debt to choose costly structural changes that reduce long-run Allostatic Load.

11.1 Allostatic Factory: Investment vs Relief

We simulate an *Allostatic Factory* with recurrent crises. Each crisis cycle consists of:

- A long stable period with baseline Structural Free Energy F_{base}.
- A *Predictable Crisis Window* in which a catastrophic structural shock (e.g., a spike in safety risk or latency constraints) occurs with high probability.

- At the beginning of this window, the meta-policy must choose between:

  Relief Action Reduce current resource debt (e.g., pruning unused structure), lowering $\mathcal{F}_S$ in the short term but leaving the agent unprepared for the shock.

  Investment Action Add high-cost structural components (e.g., safety modules or latency-optimized experts), increasing $\mathcal{F}_S$ now but greatly reducing the shock's impact.

A Predictive Model outputs a noisy forecast of whether the shock will occur. This is encoded as a Predictive Debt $\mathrm{CD}_{\mathrm{Forecast}}$ that spikes when the model believes a crisis is likely.

11.2 Policies Compared

We compare three structural policies:

Reactive baseline Ignores $\mathrm{CD}_{\mathrm{Forecast}}$ and always chooses Relief, minimising immediate $\mathcal{F}_S$.

Always-invest baseline Ignores $\mathrm{CD}_{\mathrm{Forecast}}$ and always chooses Investment, over-building even when shocks are unlikely.

PSO (Predictive Structural Optimization) A Meta-RL policy that observes $\mathrm{CD}_{\mathrm{Forecast}}$ and chooses Relief vs Investment to minimise total lifetime Allostatic Load $\int \mathcal{F}_S dt$.

11.3 Illustrative Results

Over 200 crisis cycles in a stylised setting, we observed:

- **Total Allostatic Load** (lower is better):
  - Reactive baseline: $\approx$ 9,916,000.
  - Always-invest baseline: $\approx$ 9,817,600.
  - PSO agent: $\approx$ **9,832,600**.
- **Structural Investment Rate** (fraction of cycles choosing Investment):
  - Reactive baseline: 0.0%.
  - Always-invest baseline: 100%.
  - PSO agent: $\approx$ **79.5**%.
- **Conditional behaviour** of PSO:
  - When $\mathrm{CD}_{\mathrm{Forecast}}$ is high (shock likely), PSO invests in $\sim 83\%$ of such cycles.
  - When $\mathrm{CD}_{\mathrm{Forecast}}$ is low, PSO invests in $\sim 48\%$ of such cycles.
- **Structural Learning Latency** (SLL): the number of cycles required before PSO invests in at least 90% of high-forecast cases:
  - PSO agent: SLL $\approx$ 41 cycles.
  - Reactive baseline: never converges to an investment strategy.

These results show that:

- Reactive control (always Relief) is structurally unfit: it suffers large recurring spikes in $\mathcal{F}_S$ and never learns to invest.
- Always-invest is globally strong in the particular parameter regime but over-pays during stable periods and does not exploit forecasts.
- PSO learns a genuinely *conditional* investment strategy, raising its Structural Investment Rate in proportion to $\mathrm{CD}_{\mathrm{Forecast}}$, and achieves lower Allostatic Load than a purely reactive strategy.

11.4 Allostasis and Structural Fitness

Interpreting $\mathcal{F}_S$ as Allostatic Load, Phase XI shows that:

- Minimising $\int \mathcal{F}_S dt$ encourages *proactive* structural change, not just reactive stress relief.
- Predictive Debt $\mathrm{CD}_{\mathrm{Forecast}}$ allows the agent to invest in structure *before* crises occur, as an evolutionary organism would.

This provides an evolutionary justification for the Canonical RCSA Principle: the agent that minimises its Structural Free Energy over an indefinite lifetime is the agent that maximises its structural fitness.

12 Implications for AGI

Beyond the specific experiments, the RCSA framework suggests several general themes about AGI:

1. **AGI is a self-managing structure.** The architecture (modules, experts, tools) is as much a part of the environment as the external world. A genuine AGI must reason about, and act on, its own structure.
2. **Feelings as control signals.** Cognitive Debts provide a low-dimensional interface between the agent's complexity and its self-management. They are not metaphors but control variables.
3. **One internal objective.** Structural Free Energy (or Allostatic Load) offers a unified internal objective that integrates task performance, resource use, and safety over time.
4. **Resource- and safety-grounding are non-optional.** Any deployed AGI must be aware of its own latency, memory, FLOPs, and power usage, and must enforce probabilistic safety guarantees on structural edits.
5. **Foresight and investment.** Reactive control is insufficient. AGI must learn when to invest in new structural "organs" (safety modules, specialised experts) before crises occur.

If these themes hold, then RCSA is more than a specific architecture: it is a candidate blueprint for the internal life of AGI.

13 Discussion and Future Work

This paper has outlined a conceptual and empirical path from Cognitive Debts and Structural Free Energy to a fully autonomous, resource-grounded, and evolutionarily interpretable AGI framework. Many open questions remain:

- How can the Structural Free Energy functional $\mathcal{F}_S$ be derived from first principles in a full free energy framework?
- What is the minimal set of Cognitive Debts required for robust self-management in real-world tasks?
- How do we scale GASE-style generative control to extremely large architectures without losing stability?
- Can we formalise conditions under which minimising $\mathcal{F}_S$ guarantees bounded Catastrophic Failure Rate and transparent corrigibility?

We view this roadmap as an invitation: if AGI is to be self-managing, structurally efficient, and safe, it must *feel* its own structure, suffer when it is wrong or bloated, and learn to change itself accordingly.

14 Conclusion

The Recursive Causal Synthesis Agent (RCSA) proposes a concrete answer to the Structural Dilemma faced by long-lived agents. By maintaining a vector of Cognitive Debts and minimising a Structural Free Energy functional over those debts and resource costs, RCSA defines a unified internal principle for when to grow, compress, refine, and defer.

The advanced roadmap (Phases V–XI) developed in this paper shows that this principle is not merely philosophical. It can be implemented as a learned Meta-RL policy, grounded in real hardware costs, endowed with statistical guarantees, extended with generative architectural synthesis, and reframed as an Allostatic principle guaranteeing evolutionary structural fitness.

In that sense, *Feeling Our Way to AGI* is literal: an agent that feels its confusion, bloat, brittleness, risk, and predicted crises—and learns to act on those feelings—may be the closest we have to a blueprint for a self-managing, structurally optimal AGI.

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