# Life as a Stochastic Oscillator: Resilience, Control, and the Asymmetric Integral of Meaning

Jayanth Kumar JayKmr jayanthjaiswal15@gmail.com

October 19, 2025

#### Abstract

We formalize an intuitive metaphor of life as an oscillation between joy and pain by developing a stochastic dynamical model with resilience and control. The instantaneous "life level" y(t) evolves as a driven stochastic differential equation (SDE), while a latent resilience state R(t) increases under adversity and decays otherwise. We define a path functional of fulfillment that integrates rectified joy, penalized pain, and resilience-weighted engagement. This framework connects ideas from control, thermodynamics (entropy budgets), information (free-energy objectives), game theory (Nash-like trade-offs), ergodicity, and network synchronization. We provide closed-form calculations for rectified Gaussian expectations, exhibit qualitative phase behavior, and release a reference simulation that illustrates policy trade-offs among (i) tempered engagement, (ii) joy-chasing, and (iii) avoidance. Our thesis is that meaning is not the time-average baseline but an asymmetric integral over shaped, noisy trajectories, where agency converts volatility into significance without courting ruin.

#### 1 Introduction

Hedonic experience oscillates. Periods of elation are contrasted by troughs of suffering; randomness perturbs timing and depth. Common counsel to "minimize pain" often suppresses peaks as well, flattening life. Conversely, thrill-seeking heightens variance and tail risk. We recast these observations into a tractable mathematical model where (i) a baseline  $\mu$  sets the center of gravity, (ii) oscillation amplitude A and cadence  $\omega$  shape deterministic cycles, (iii) volatility  $\sigma$  injects randomness, (iv) resilience R(t) accumulates through recovery, and (v) actions u(t) modulate parameters at energetic cost. The value of a life path is an integral that counts joy asymmetrically, penalizes pain, and rewards engaged effort proportional to resilience.

Contributions. (1) A coupled SDE-ODE for life and resilience; (2) a fulfillment functional with closed-form Gaussian rectification; (3) a control formalism against entropy; (4) an ergodicity-aware

evaluation emphasizing time-average growth; (5) community coupling via a Kuramoto-style phase model; (6) a reference implementation with interpretable diagrams.

#### 2 Related Work

Our formulation synthesizes strands from stochastic control [Yong and Zhou, 1999], risk-sensitive objectives [Whittle, 1990], free-energy principles in cognition [Friston, 2010], antifragility [Taleb, 2012], and synchronization dynamics [Strogatz, 2000]. We do not claim novelty in the components but in their assembly toward an operational lens on meaning-making.

#### 3 Deterministic Oscillator

Consider

$$y(t) = \mu + A\sin(\omega t + \varphi),\tag{1}$$

with baseline  $\mu \in \mathbb{R}$ , amplitude  $A \geq 0$ , frequency  $\omega > 0$ , and phase  $\varphi \in \mathbb{R}$ . Over a period  $T = 2\pi/\omega$ , the mean is  $\overline{y} = \mu$ . The fraction of time above zero is

$$p_{+} = \frac{1}{2} + \frac{1}{\pi} \arcsin\left(\frac{\mu}{A}\right), \quad \text{for } |\mu| < A, \tag{2}$$

clamped to [0,1] for  $|\mu| \geq A$ . The mean positive half-wave (with  $\mu = 0$ ) is  $A/\pi$  per unit time.

## 4 Stochastic Dynamics

We incorporate noise via

$$dy_t = \left[\mu + A\sin(\omega t + \varphi)\right]dt + \sigma dW_t,\tag{3}$$

where  $W_t$  is a Wiener process and  $\sigma \geq 0$ . The drift preserves the deterministic skeleton; diffusion drives random excursions.

#### 4.1 Resilience Dynamics

Resilience grows under adversity and decays otherwise:

$$\dot{R}(t) = \alpha \max(-y(t), 0) - \beta R(t), \quad \alpha, \beta > 0.$$
(4)

This captures "use it or lose it": when below baseline, recovery practice reinforces capacity; unused capacity dissipates.

#### 5 The Fulfillment Functional

We define instantaneous utility

$$u(y, R; \lambda, \rho) = \max(y, 0) - \lambda \max(-y, 0) + \rho R |y|, \tag{5}$$

with  $\lambda \geq 1$  penalizing pain asymmetrically and  $\rho \geq 0$  rewarding engagement modulated by resilience. The fulfillment over [0,T] is

$$\mathcal{F}[0,T] = \int_0^T u(y(t), R(t); \lambda, \rho) \, \mathrm{d}t. \tag{6}$$

#### 5.1 Closed-Form Rectification under Gaussianity

At time t, if  $y \sim \mathcal{N}(m, \sigma^2)$  with  $m = \mu + A\sin(\omega t + \varphi)$  and  $\kappa = m/\sigma$ , then

$$\mathbb{E}[(y)_{+}] = \sigma \,\phi(\kappa) + m \,\Phi(\kappa),\tag{7}$$

$$\mathbb{E}[(y)_{-}] = \sigma \,\phi(\kappa) - m \,\Phi(-\kappa),\tag{8}$$

where  $\phi$ ,  $\Phi$  are the standard normal pdf/cdf. Substituting Eq. (8) into Eq. (5) yields  $\mathbb{E}[u(y,R)]$  given  $\mathbb{E}[R]$ .

### 6 Control Against Entropy

Let actions u(t) reshape parameters  $(\mu, A, \omega, \sigma)$  with cost c(u). The agent maximizes

$$\max_{u(\cdot)} \mathbb{E}\left[\mathcal{F}[0,T]\right] - \int_0^T c(u(t)) dt$$
 (9)

subject to Eqs. (3)–(4). This induces a Hamilton–Jacobi–Bellman equation over state x = (y, R) with running reward u(y, R).

Thermodynamic guardrails. (i) Fluctuation-dissipation: variance reduction requires energetic expenditure (buffers, routines). (ii) Landauer: erasing errors/memories has a minimum cost. Sustained increases to  $\mu$  or reshaping  $A, \omega, \sigma$  are energetically non-free.

# 7 Ergodicity and Tail-Risk

Time-average growth can differ from ensemble averages. For multiplicative capital (career, trust, health), downside volatility depresses time-average growth (Jensen). This favors policies that cap left-tail risk over those that only chase right-tail extremes.

### 8 Social Coupling

For N individuals with phases  $\theta_i$ , a Kuramoto-style coupling reads

$$\dot{\theta}_i = \omega_i + \frac{K}{N} \sum_{i=1}^N \sin(\theta_i - \theta_i), \quad y_i = \mu_i + A_i \sin \theta_i + \sigma_i \dot{W}_i.$$
 (10)

Moderate coupling K supports phase alignment (mutual aid); too much synchrony yields herd risk.

### 9 Diagrams

#### 9.1 Oscillation and Rectification

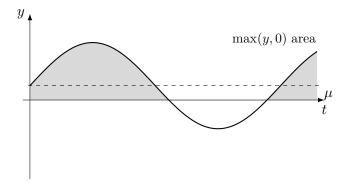


Figure 1: Deterministic oscillation with baseline  $\mu$  and positive rectification. Shaded area contributes to the joy term in Eq. (5).

#### 9.2 Block Diagram of the Model

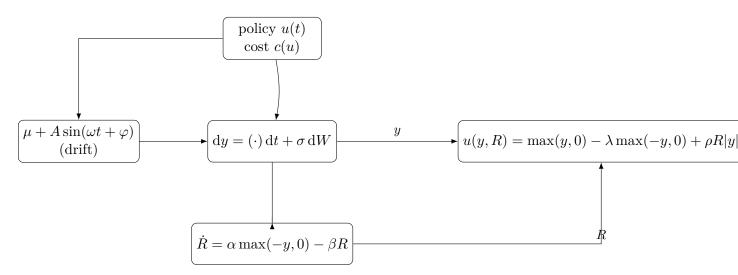


Figure 2: Block diagram: drifted SDE for y, resilience ODE for R, asymmetric utility and integral fulfillment with a control loop.

#### 9.3 Qualitative Phase Portrait

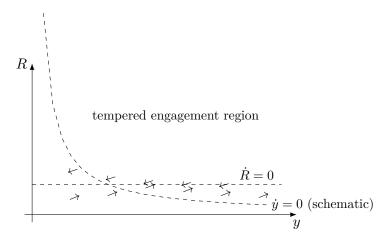


Figure 3: Schematic (y, R) phase portrait: resilience accumulates in downturns, decays otherwise; tempered regions avoid ruin while enabling growth.

#### 10 Simulation

We implement Euler—Maruyama for the life SDE and forward Euler for resilience, comparing three policies: tempered engagement (moderate variance, strong resilience), joy-chasing (high variance, weak resilience), and avoidance (low variance, little growth).

#### Core simulation code (Python)

Listing 1: Core simulation loop (Euler–Maruyama + resilience ODE).

```
import numpy as np
def simulate(mu,A,omega,phi,sigma,alpha,beta,lam,rho, T=50.0, dt=0.01, N=384, seed=123):
   rng = np.random.default_rng(seed)
   steps = int(T/dt)
   t = np.linspace(0.0, T, steps+1)
   y = np.zeros((steps+1, N)); R = np.zeros((steps+1, N))
   drive = mu + A*np.sin(omega*t + phi)
   sqrt_dt = np.sqrt(dt)
   for k in range(steps):
       dW = rng.normal(0.0, sqrt_dt, size=N)
       y[k+1] = y[k] + drive[k]*dt + sigma*dW
       neg = np.maximum(-y[k], 0.0)
       R[k+1] = R[k] + (alpha*neg - beta*R[k])*dt
   pos = np.maximum(y,0.0); neg = np.maximum(-y,0.0)
   inst = pos - lam*neg + rho*R*np.abs(y)
   Fcum = np.cumsum(inst*dt, axis=0)
   return t, y, R, Fcum
```

### **Figures**

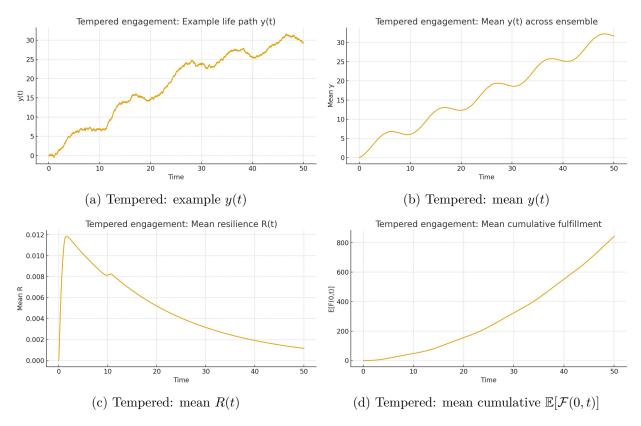


Figure 4: Tempered engagement scenario.

Table 1: Ensemble simulation summary across scenarios (T = 50). Metrics are averaged over paths and time where applicable.

Scenario	$\operatorname{Avg} y$	$\operatorname{Avg}R$	Time $> 0$ (fraction)	$\mathbb{E}[\text{Final Fulfillment}]$
Tempered engagement	16.833	0.005	0.995	842.218
Joy-chasing (high variance)	14.932	0.033	0.978	746.934
Avoidance (low variance, flat)	14.281	0.0	0.999	714.172

#### 10.1 Summary table

The CSV artifact (Life\_Simulation\_\_\_Scenario\_Summary.csv) is summarized in Table 1.

# 11 Analytic Notes

**Proposition 1** (Expected positive part under Gaussianity). Let  $Y \sim \mathcal{N}(m, \sigma^2)$ . Then  $\mathbb{E}[(Y)_+] = \sigma \phi(m/\sigma) + m \Phi(m/\sigma)$  and  $\mathbb{E}[(Y)_-] = \sigma \phi(m/\sigma) - m \Phi(-m/\sigma)$ .

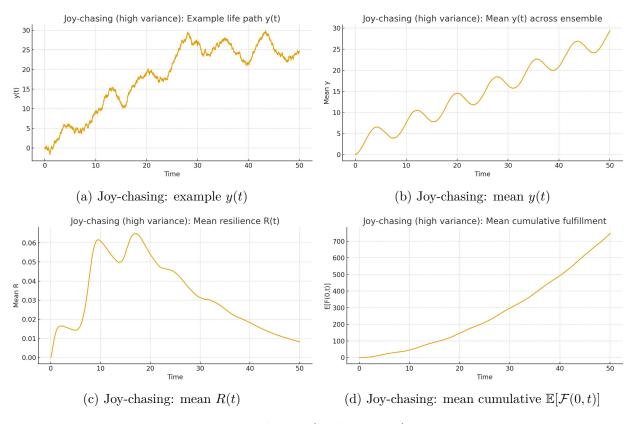


Figure 5: Joy-chasing (high variance) scenario.

*Proof.* Immediate from symmetry and integration by parts using the identity  $\mathbb{E}[\max(Y,0)] = \int_0^\infty \Pr(Y>y) \,dy$  and the Mills ratio.

# 12 Life as a Nash Equilibrium Against Entropy

We cast the agent's shaping of  $(\mu, A, \omega, \sigma)$  as a continuous-time differential game with an adversary we call "entropy," which injects volatility and dissipation. Let the agent choose a policy u and the adversary choose disturbances v that tilt variance and drag (e.g., via effective  $\sigma(v)$  and costs  $c_v(v)$ ). Consider the payoff

$$J(u,v) = \mathbb{E}\left[\mathcal{F}[0,T]\right] - \int_0^T \left(c_u(u_t) + c_v(v_t)\right) dt, \tag{11}$$

with dynamics as before but with diffusion and dissipation shaped by (u, v). A (feedback) Nash equilibrium  $(u^*, v^*)$  satisfies

$$J(u^*, v^*) \ge J(u, v^*), \qquad J(u^*, v^*) \le J(u^*, v), \qquad \forall u, v.$$
 (12)

No unilateral "joy only" optimum. Setting  $A\downarrow 0$  (flattening swings to avoid pain) reduces negative excursions but also eliminates positive peaks. With utility u(y,R) in Eq. (5), the expected rectified gain under Gaussian slices obeys  $\mathbb{E}[(y)_+] = \sigma \phi(\kappa) + m \Phi(\kappa)$ ; if  $A \to 0$  then  $m = \mu$  is

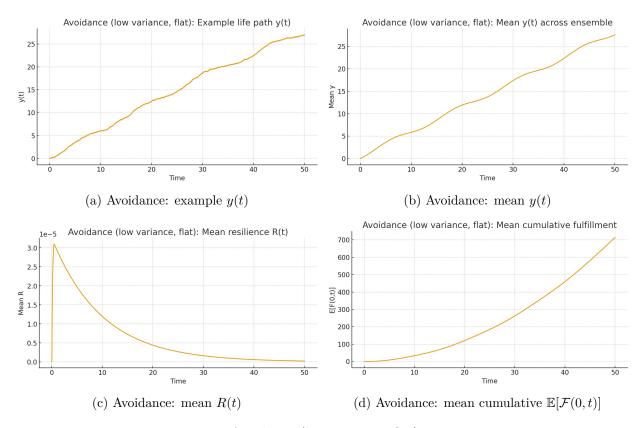


Figure 6: Avoidance (low variance, flat) scenario.

constant and the oscillatory contribution vanishes. Thus, suppressing variance drives the waveform toward baseline  $\mu$ , forfeiting the contrast that amplifies meaning.

No unilateral "peaks only" optimum. Conversely, blowing up A or  $\sigma$  invites large  $\mathbb{E}[(y)_{-}]$  and increases the pain penalty  $\lambda \mathbb{E}[(y)_{-}]$ , while degrading time-average growth via left tails (ergodicity loss). Pursuit of pure highs destabilizes the system and lowers  $\mathbb{E}[\mathcal{F}]$  once costs and ruin risk are accounted for.

Equilibrium intuition. Best responses balance amplitude with recovery: increase A only to the extent that resilience R(t) and downside protection bind left tails. The fixed point of agent incentives (raising structure and resilience) against entropy (injecting noise and drag) is a tempered engagement policy. In Isaacs/HJB terms, stationarity occurs when the marginal benefit of variance for rectified gains equals the marginal pain/cost, adjusted by the marginal increase in the resilience conversion term  $\rho R|y|$ .

**Proposition 2** (Informal Nash law of meaning). In the differential game (11), under standard coercivity and convexity/concavity assumptions on costs and diffusion shaping, any feedback Nash equilibrium  $(u^*, v^*)$  avoids both variance-zeroing  $(A = 0, \sigma = 0)$  and variance-exploding  $(A, \sigma \to \infty)$ . Equilibrium policies keep nonzero amplitude and bounded volatility while allocating effort to resilience, thereby integrating joy and pain rather than isolating either.

**Practical corollary.** Strategies that chase pure highs (maximize A while ignoring R and tail risk) or chase pure comfort (minimize A toward numbness) are both dominated by tempered policies that invest in recovery, cap ruin, and preserve enough variance for contrast. In short: no optimal strategy isolates joy—equilibrium demands integrating both, as pain's contrast amplifies meaning.

#### 13 Discussion

Our results suggest that policies which (i) raise baseline  $\mu$ , (ii) right-size amplitude A instead of suppressing it, (iii) cap left tails, and (iv) invest in resilience R convert volatility into fulfillment more effectively than either thrill-seeking or avoidance. Community coupling can further stabilize phases but invites herd risk if excessive.

#### 14 Limitations and Extensions

We used a sinusoidal driver for interpretability; real dynamics may be multi-frequency or regimeswitching. Extending to jump diffusions can capture shocks. Richer learning rules for R(t) (e.g., saturating growth, delayed reinforcement) merit study. Empirical validation requires longitudinal data and careful identification strategies.

#### 15 Conclusion

Mathematically, we framed "meaning" as an asymmetric integral over a shaped, noisy process: a baseline  $\mu$  you can responsibly raise, an amplitude A you should right-size rather than suppress, a cadence  $\omega$  you can ritualize, volatility  $\sigma$  you cannot avoid but can harness, a resilience state R(t) that remembers recovery, and an intention u(t) that steers all of the above under real energetic costs. ewline **Spiritually**, the same structure can be read as a compact liturgy of living:

- 1. Baseline  $\mu$  as equanimity.  $\mu$  is the felt center of a life—steadiness, trust, and groundedness. It grows through humble practices: sleep, honest work, prayer/meditation, unhurried friendship, stewardship of the body. Raising  $\mu$  is not a hack; it is fidelity to what is simple and true.
- 2. **Amplitude** A **as the capacity to love.** Large A means you are moved by the world; too small and you risk numbness, too large and you risk burnout. Courage and compassion increase A with skillful containment: boundaries, confession, and rest keep love from turning into exhaustion.
- 3. Cadence  $\omega$  as rhythm and Sabbath. Without rhythm, fluctuations interfere destructively. Rituals—weekly rest, shared meals, walks, liturgy, art—phase-lock attention to what matters, letting peaks recover and troughs heal.
- 4. Volatility  $\sigma$  as impermanence and grace. Randomness reminds us we are not sovereign. One cannot choose  $\xi(t)$ , but one can choose a stance: curiosity over fear, gratitude over grasping. Grace often arrives as an unplanned cross-term.

- 5. Resilience R(t) as the heart's memory of recovery. R grows when we do not flee the valley: lament, reflection, therapy, forgiveness, community, and service metabolize pain into wisdom. Unused, R decays; the soul deconditions without practice.
- 6. Control u(t) as intention—and its complement, surrender. Discipline shapes  $\{\mu, A, \omega, \sigma\}$ , but every control loop needs an outer loop: relinquishment to reality/God/Nature. Strategy without surrender becomes violence; surrender without strategy becomes drift.
- 7. **Coupling as communion.** Phase alignment with others—family, neighbors, choir, team—amplifies good and buffers harm. Yet herd dynamics can stampede; ethical leadership modulates coupling so that solidarity does not become frenzy.

Ethical guardrails. This model acknowledges that suffering can deepen R; it does not romanticize harm. We must not instrumentalize pain in ourselves or others. Protect left tails (no ruin); resist systems that manufacture avoidable suffering; let recovery be as intentional as challenge.

**Practices that integrate the waveform.** Attend (daily examen/journaling), align (rituals that set  $\omega$ ), strengthen (habits that raise  $\mu$ ), widen (compassion that right-sizes A), insure (policies that cap downside), serve (coupling that shares load). In symbols: turn randomness into resonance by investing where R(t) is formed and where u(t) is most leveraged.

**Closing.** Hold the mathematics lightly and the persons firmly. Let the measure be mercy, the method be attention, and the model a humble map. Integrate the full waveform; receive the noise as teacher; convert volatility into love without courting ruin.

**Artifacts.** Simulation code and data accompany this manuscript.

**Ethics Statement.** This paper is metaphorical and normative; it is not mental-health advice. Interventions should be undertaken with professional support.

# Acknowledgments

Thanks to collaborators and readers for critique and inspiration.

#### References

Jiongmin Yong and Xun Yu Zhou. Stochastic Controls: Hamiltonian Systems and HJB Equations. Springer, 1999.

Peter Whittle. Risk-Sensitive Optimal Control. Wiley, 1990.

Karl Friston. The free-energy principle: a unified brain theory? *Nature Reviews Neuroscience*, 11(2):127–138, 2010.

Nassim Nicholas Taleb. Antifragile: Things That Gain from Disorder. Random House, 2012.

Steven H. Strogatz. From Kuramoto to Crawford: exploring the onset of synchronization in populations of coupled oscillators. *Physica D*, 143(1–4):1–20, 2000.

#### A Parameter Sensitivities

Differentiating  $\mathbb{E}[(Y)_+]$  w.r.t. m yields  $\partial_m \mathbb{E}[(Y)_+] = \Phi(m/\sigma)$  (smooth soft-rectifier). This clarifies how raising  $\mu$  boosts expected joy more strongly when currently near/below zero.

### **B** Suggested Categories

Quantitative Methods (q-bio.QM), Statistical Mechanics (cond-mat.stat-mech), Optimization and Control (math.OC), and Systems and Control (eess.SY).