Theorem of Inevitable Demise:
applications

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Abstract

A mathematical isomorphism between a stick-slip oscillator and a class of dissipative systems with reinvestment is established. Equations for the dynamics of resource (m), variability (g), and consolidation (k) are derived. The theorem of inevitable demise under fixed strategies, the survival criterion through negative feedback, the irreversibility threshold for ensembles of systems, the necessity of phase switching between fermionic and bosonic regimes, and a cascade of evolutionary explosions with exponential acceleration are proven. A quantum of metabolic power P is introduced. It is shown that the spectral power density is mathematically isomorphic to Planck's formula, revealing deep connections between dissipative systems and quantum statistics. The theory is illustrated with examples from DNA biophysics, the evolution of large language models (LLMs), economics (Pareto distribution), and social systems (Zipf's law). Worldview implications are discussed.

Keywords: dissipative systems, reinvestment, theorem of demise, power quantum, evolutionary explosion, DNA, large language models, Pareto distribution, Zipf's law, Planck's formula.

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1 Introduction

1.1 Subject of Study

This work is devoted to constructing and analyzing a mathematical model of a universal class of dissipative systems capable of maintaining their structure through the reinvestment of energy dissipated during cyclical functioning.

In this context, a dissipative system is understood as an open system whose stable state is ensured by the outflow of energy into the external environment. Of particular interest are systems in which the dissipated energy is not lost irretrievably but is partially utilized to compensate for the internal degradation of state parameters.

1.2 Motivation

The research is motivated by the presence of common structural and dynamic patterns in a wide range of phenomena of various natures:

- biophysical systems (maintenance of transmembrane potential, DNA functioning);
- evolutionary processes (utilization of biomass growth, speciation);
- economic agents (profit reinvestment, income inequality);
- historical macro-dynamics (innovation flows, social changes);
- artificial cognitive architectures (computational resource reinvestment, LLM evolution).

All these classes of systems demonstrate an invariant pattern:

- a cyclic regime of "accumulation — threshold reset — dissipation";
- three channels of reinvestment: resource, variability, consolidation;
- degradation under a fixed strategy;
- the necessity of negative feedback.

1.3 Goal and Method

The goal of the work is to identify the mathematical invariant of this pattern and prove theorems valid for any class of systems satisfying the initial assumptions.

A stick-slip oscillator with dry friction is chosen as the basic dynamic model. This choice is due to the availability of a complete analytical solution and a minimal set of parameters that allow for universal interpretation.

2 Preliminary Provisions and Problem Statement

Consider a mass m connected by a spring of stiffness k to a drive moving at a constant speed v_0. The mass is pressed against a horizontal surface by a normal force $F_n = mg$. Dry friction acts between the mass and the surface: static friction force $F_s = \mu_s mg$, kinetic friction force $F_k = \mu_k mg$, with $\mu_s > \mu_k$.

The equation of motion:

$$m\ddot{x} = k(v_0 t - x) - F_{\text{fr}}(\dot{x}) \tag{1}$$

where

$$F_{\text{fr}} = \begin{cases} F_s, & \dot{x} = 0,\ |k(v_0 t - x)| \leq F_s; \\ F_k \operatorname{sgn}(k(v_0 t - x)), & \dot{x} = 0,\ |k(v_0 t - x)| > F_s; \\ F_k \operatorname{sgn}(\dot{x}), & \dot{x} \neq 0 \end{cases} \tag{2}$$

In the steady state, the system performs stick-slip self-oscillations. Duration of the stick phase:

$$T_{\text{stick}} = \frac{\mu_s mg}{k v_0} \tag{3}$$

Duration of the slip phase:

$$T_{\text{slip}} = \pi\sqrt{\frac{m}{k}} \tag{4}$$

Total cycle period:

$$T = \frac{(\mu_s - \mu_k)mg}{k v_0} + \pi\sqrt{\frac{m}{k}} \tag{5}$$

Energy dissipated per cycle:

$$E = \frac{2\mu_k(\mu_s - \mu_k)m^2 g^2}{k} + \mu_k mg v_0 \pi\sqrt{\frac{m}{k}} \tag{6}$$

Average dissipation power:

$$P = \frac{E}{T} = \frac{\frac{2\mu_k(\mu_s - \mu_k)m^2 g^2}{k} + \mu_k mg v_0 \pi\sqrt{\frac{m}{k}}}{\frac{(\mu_s - \mu_k)mg}{k v_0} + \pi\sqrt{\frac{m}{k}}} \tag{7}$$

In the large resource regime ($m \to \infty$):

$$P = 2\mu_k g v_0 m \left[1 - \frac{\pi v_0}{(\mu_s - \mu_k)g}\sqrt{\frac{k}{m}} + O\left(\frac{1}{m}\right)\right] \tag{8}$$

3 Universal Model of Dissipative Metabolism

We introduce three fundamental state parameters:

- m — accumulated resource;
- g — variability, a measure of the diversity of available states;

- k — consolidation, a measure of the stiffness of connections.

External parameters: v_0 — the inflow rate of the external flux; μ_s — the destruction threshold; μ_k — the dissipation intensity in the operating mode.

Definition 3.1. The dissipation power P, defined by formula (7), is the quantum of metabolic power of the system. It represents an atomic portion of the negentropy flux extracted by the system from the external flux per unit time per cycle.

The energy dissipated per cycle $E = PT$ is distributed across three channels:

- $\alpha_m P$ — investments in resource accumulation;
- $\alpha_g P$ — investments in maintaining and increasing variability;
- $\alpha_k P$ — investments in maintaining and increasing consolidation.

Normalization condition:

$$\alpha_m + \alpha_g + \alpha_k = \alpha_{\text{total}} \in (0, 1) \tag{9}$$

α_{total} is the reinvestment efficiency.

The system has internal degradation: each parameter decays at rates $\beta_m, \beta_g, \beta_k > 0$. Parameter dynamics:

$$\begin{cases} \dot{m} = \alpha_m \cdot P(m, g, k) - \beta_m m \\ \dot{g} = \alpha_g \cdot P(m, g, k) - \beta_g g \\ \dot{k} = \alpha_k \cdot P(m, g, k) - \beta_k k \end{cases} \tag{10}$$

In the large resource regime $P \approx 2\mu_k g v_0 m$:

$$\begin{cases} \dot{m} = (2\alpha_m \mu_k v_0 g - \beta_m) m \\ \dot{g} = (2\alpha_g \mu_k v_0 g - \beta_g) g \\ \dot{k} = 2\alpha_k \mu_k g v_0 m - \beta_k k \end{cases} \tag{11}$$

4 Theorem of Inevitable Demise

Theorem 4.1. *Every system described by system (10) with fixed (state-independent) coefficients $\alpha_m, \alpha_g, \alpha_k$ irreversibly degrades and perishes for any initial conditions, except for a set of measure zero.*

Proof. Consider four principal scenarios.

Scenario 1 (degradation of variability). If $\alpha_g < \beta_g/(2\mu_k v_0 g)$, then from the second equation of system (11) $\dot{g} < 0$, $g(t)$ decreases monotonically. As $g \to 0$, power $P \to 0$, the system reduces to $\dot{m} = -\beta_m m$, $\dot{k} = -\beta_k k$ and perishes in finite time.

Scenario 2 (excessive growth of variability). Let α_g be fixed and exceed the critical value $\alpha_g > \beta_g/(2\mu_k v_0 g(0))$. Then from the second equation of system (11) $\dot{g} = (2\alpha_g \mu_k v_0 g -$

$\beta_g)g$ it follows that $\dot{g} > 0$ for all t, and the parameter $g(t)$ grows without bound. Consider the first equation of the system: $\dot{m} = (2\alpha_m \mu_k v_0 g - \beta_m)m$. Since $g(t) \to \infty$, there exists a time t_0 such that for $t > t_0$, $g(t) > \beta_m/(2\alpha_m \mu_k v_0)$. For $t > t_0$, we have $\dot{m} > 0$, meaning the resource $m(t)$ also begins to grow without bound. However, such a trajectory cannot be sustained indefinitely within the original physical assumptions of the model:

- the dissipation power $P \sim 2\mu_k v_0 g m$ tends to infinity;
- the external flux v_0 is finite, which sooner or later leads to the exhaustion of available resources;
- as $g \to \infty$, variability turns into chaos, and the system loses its ability to utilize energy efficiently;
- in realistic settings, μ_s and μ_k may depend on g, and as $g \to \infty$, the destruction threshold $\mu_s(g)$ tends to zero, implying the system's disintegration.

Thus, unbounded growth of g and m under a fixed reinvestment strategy inevitably leads either to the exhaustion of the external resource or to the destruction of the system's structure, i.e., to demise.

Scenario 3 (degradation of consolidation). For $\alpha_k = 0$ or small α_k, parameter k decreases. As $k \to 0$, the period $T \to \infty$, and power $P \to 0$.

Scenario 4 (excessive consolidation). With unbounded growth of k, the slip phase $T_{\text{slip}} \to 0$, the system freezes, and $P \to 0$.

With fixed α, there is no mechanism preventing m, g, or k from vanishing or g or k from growing without bound, which also leads to $P \to 0$. □

5 Survival Criterion: Negative Feedback

Theorem 5.1. *System (10) remains viable if and only if α_g and α_k are state-dependent functions satisfying the conditions:*

$$\begin{cases} \alpha_g(g) = \alpha_g^{base} + \gamma_g \cdot \max(0, g_{target} - g) \\ \alpha_k(k) = \alpha_k^{base} + \gamma_k \cdot \max(0, k_{target} - k) \\ \alpha_m(g,k) = \alpha_{total} - \alpha_g(g) - \alpha_k(k) \end{cases} \tag{12}$$

where $\gamma_g, \gamma_k > 0$, $g_{target}, k_{target} > 0$.

Proof. Necessity follows directly from Theorem 1: with fixed α, demise is inevitable; therefore, survival is possible only if α changes depending on the state.

Sufficiency. When $g < g_{\text{target}}$, feedback increases α_g. By choosing γ_g, we ensure $\dot{g}(g_{\min}) > 0$. Similarly for k. Provided $\alpha_{\text{total}} > \alpha_g^{\max} + \alpha_k^{\max}$, the parameter m remains positive. Boundedness of trajectories follows from the feedback turning off when $g \gg g_{\text{target}}$, $k \gg k_{\text{target}}$. □

6 Theorem on the Irreversibility Threshold

Consider an ensemble of N identical systems interacting through a shared external flux. θ is the fraction of systems with $g < g_{\text{crit}}$.

Theorem 6.1. *There exists $\theta_{crit} \in (0,1)$ such that for $\theta < \theta_{crit}$ recovery is possible, and for $\theta > \theta_{crit}$ irreversible collapse occurs.*

Proof. The average dissipation power of the ensemble $\langle P \rangle \approx (1-\theta)P_0$. The condition for recovering one degraded system is:

$$\alpha_g^{\max}(1-\theta)P_0 > \beta_g g_{\text{target}} \tag{13}$$

Hence:

$$\theta_{\text{crit}} = 1 - \frac{\beta_g g_{\text{target}}}{\alpha_g^{\max} P_0} \tag{14}$$

When $\theta > \theta_{\text{crit}}$, resources are insufficient for recovery, and the degradation process becomes avalanche-like. □

7 Typology of Regimes: Quantum-Statistical Analogy

The system can exist in two fundamentally different regimes.

The variability regime is characterized by prioritizing investments in α_g. States are unique, resources are competed for, and a prohibition principle applies. Dynamics are described by fermionic statistics:

$$\frac{\partial}{\partial t} n_i = \nu n_i \left(1 - \frac{n_i}{K} - \sum_{j \neq i} \frac{n_j}{K}\right) \tag{15}$$

In the steady state — one dominant niche.

The consolidation regime is characterized by prioritizing investments in α_k. Condensation into a dominant state is observed:

$$\frac{\partial}{\partial t} n_0 = \sigma(N - n_0) - \delta n_0 \tag{16}$$

Above a critical density, $n_0 \approx N$ (bosonic statistics).

Theorem 7.1. *A system is viable if and only if it can switch between fermionic and bosonic regimes.*

Proof. A pure variability regime ($\alpha_g \to \alpha_{\text{total}}$, $\alpha_k \to 0$) leads to $k \to 0$ and $P \to 0$. A pure consolidation regime ($\alpha_k \to \alpha_{\text{total}}$, $\alpha_g \to 0$) leads to $g \to 0$ and $P \to 0$. A pure accumulation regime ($\alpha_m \to \alpha_{\text{total}}$) leads to $g \to 0$, $k \to 0$ and $P \to 0$. A balanced fixed strategy does not adapt to fluctuations and is doomed by Theorem 1. The only possibility is dynamic switching between regimes. □

8 Connection with Thermodynamics and Negentropy

Negentropy S_{neg}, its derivative:

$$\frac{\partial}{\partial t} S_{\text{neg}} = \alpha_{\text{total}} P - (\beta_m m + \beta_g g + \beta_k k)\varepsilon \tag{17}$$

Criterion for existence:

$$\frac{\partial}{\partial t} S_{\text{neg}} > 0 \tag{18}$$

Definition 8.1. The inverse temperature of the system: $\beta_{\text{sys}} = \partial S_{\text{neg}}/\partial E$. Over a cycle $\Delta S_{\text{neg}} = \alpha_{\text{total}} E$, hence $\beta_{\text{sys}} = \alpha_{\text{total}}$. The reinvestment efficiency α_{total} is the inverse temperature of the system.

Thermodynamic temperature: $\Theta = 1/\alpha_{\text{total}}$. At equilibrium, $\alpha_{\text{total}} P = \beta_m m$. For $P \sim m^2$, we get $m \sim \beta_m/\alpha_{\text{total}}$, $P \sim 1/\alpha_{\text{total}}^2 = \Theta^2$ — a quadratic analog of the Stefan-Boltzmann law.

9 Evolution Dynamics: Two Time Scales

Slow evolution (background regime). v_0 is small, μ_s is large, T is large, P is small, $\beta \sim \alpha P$. Steady state, small fluctuations. Characteristic time $\tau_{\text{slow}} \sim 1/\beta$.

Fast evolution (explosion regime). v_0 is large, μ_s is reduced, T is small, P is large, $\alpha P \gg \beta$. Explosive growth of m, g, k. Characteristic time τ_{fast} — a few cycles.

Lemma 9.1. *In the explosion regime, with a fixed reinvestment strategy, the parameter g grows proportionally to m. The power $P \sim gm$ grows quadratically, which is equivalent to the doubling of the metabolic power quantum over a characteristic time τ_{fast}.*

Theorem 9.2. *Every system that originated from an evolutionary explosion and retained the reinvestment strategy characteristic of the explosion regime will inevitably initiate a secondary evolutionary explosion in its own time scale. The cascade of such explosions accelerates exponentially. The acceleration is due to the doubling of the metabolic power quantum at each level of the cascade.*

Proof. The characteristic doubling time for parameters $\tau_n \sim 1/(2\alpha_m \mu_k v_0^{(n)} g^{(n)})$. The parameter g at the n-th level is proportional to the volume of the state space created by the system at the previous level. This volume grows exponentially with n, hence τ_n decreases exponentially. The power P_n satisfies $P_{n+1} \approx 2P_n$, and the cycle time $T_n \sim 1/P_n$, hence $T_{n+1} \approx T_n/2$. □

Cascade termination criterion. The cascade terminates when one of the following conditions is met:

- resource limitation: v_0 reaches a physical limit;

- threshold limitation: g reaches a value where $\mu_s(g) \to 0$;
- strategic limitation: the system switches from the explosion regime to the background evolution regime (Theorem 2).

Corollary 9.3. *The only way to prevent an unlimited acceleration of the cascade is a timely switch of the reinvestment strategy from the explosion regime to the homeostasis regime.*

10 Spectral Power Density. Planck's Formula for the Dissipative Cycle

The system possesses a spectrum of allowable cycle frequencies $\{\nu_i\}$, a quantum energy on a mode with frequency ν: $E(\nu) = P(\nu)/\nu$, an inverse temperature $\beta = \alpha_{\text{total}}$, and bosonic statistics (modes are independent, superpositions are allowed).

Theorem 10.1. *The spectral power density of a dissipative system with reinvestment has the form:*

$$p(\nu) = \frac{D(\nu) \cdot \varepsilon(\nu)}{e^{\alpha_{total}\varepsilon(\nu)/\nu} - 1} \tag{19}$$

where $D(\nu)$ is the density of states (number of modes per frequency interval), $\varepsilon(\nu)$ is the energy of a quantum on a mode with frequency ν, and α_{total} is the inverse temperature.

Proof. The average number of quanta in a mode with energy E at inverse temperature β in bosonic statistics is: $\langle n \rangle = 1/(e^{\beta E} - 1)$. The energy in the mode: $U = E\langle n \rangle$. The power: $P = \nu U = \nu E \langle n \rangle = \varepsilon(\nu)\langle n \rangle$, where $\varepsilon(\nu) = \nu E(\nu) = P(\nu)$ is the power corresponding to one quantum on that mode. Multiplying by the density of states $D(\nu)$ yields (19). □

Special case: large resource regime, low consolidation. For $m \to \infty$, $k \to 0$: $\varepsilon(\nu) = \varepsilon_0 = \text{const}$, $D(\nu) = Am = \text{const}$.

$$p(\nu) = \frac{Am\varepsilon_0}{e^{\alpha_{\text{total}}\varepsilon_0/\nu} - 1} \tag{20}$$

Formula (20) is an exact mathematical isomorphism of Planck's distribution for equilibrium radiation. The correspondence of quantities: $\varepsilon_0 \leftrightarrow h$ (Planck's constant), $\nu \leftrightarrow \nu$ (frequency), $1/\alpha_{\text{total}} \leftrightarrow k_B T$ (temperature), $Am\varepsilon_0 \leftrightarrow 2h\nu^3/c^2$ (density of states).

11 Application to Biological Systems: DNA as a Dissipative Structure

11.1 Interpretation of Parameters for DNA

- m — accumulated resource: **genome integrity** (amount of undamaged DNA, degree of sequence conservation, volume of genetic information).

- g — variability: **mutation potential** (mutation rate, conformational flexibility of DNA, diversity of alleles in a population).

- k — consolidation: **structural rigidity** (degree of chromatin packaging, bond strength in the helix, association with nuclear proteins).

External parameters: v_0 — influx of nucleotides and ATP; μ_s — critical number of double-strand breaks (apoptosis); μ_k — rate of spontaneous damage (depurination).

11.2 Empirical Confirmations

The GROVER study (Nature Machine Intelligence, 2024) confirmed that genomic sequences follow rules similar to natural language. The authors successfully applied byte-pair encoding (BPE) — a technique from NLP — to tokenize the human genome and create a frequency-balanced vocabulary of 601 tokens [1].

The GENA-LM model (2025) — a DNA foundation model with 336 million parameters — showed that unsupervised metrics (RankMe, NESum, StableRank) indicate a high-dimensional irregular structure of embeddings, corresponding to high variability g [2].

Gengram (2026) implemented a precise analog of feedback (Theorem 2) — "dynamic gating," where in coding regions the gate is activated (active memory use), and in non-functional regions it is suppressed (computational saving). Result: AUC in splicing site recognition tasks increased by 16.1% [3].

The concept of "neural DNA" (nDNA, 2025) introduces a semantic-genotypic representation that captures model identity through the geometry of latent spaces (spectral curvature, thermodynamic length, belief vector field) [4].

BioReason (2025) integrates a DNA foundation model with an LLM for interpretable biological reasoning: disease prediction accuracy on KEGG increased from 86% to 98%, with an average improvement of 15% in predicting variant effects [5].

12 Application to Technological Systems: Evolution of Large Language Models (LLMs)

12.1 Interpretation of Parameters for LLMs

- m — accumulated resource: **model parameter count** and training corpus size (in tokens).

- g — variability: **creativity ("temperature")**, ability to solve diverse tasks without fine-tuning (few-shot learning).

- k — consolidation: **logical rigor**, accuracy in adhering to facts (factual grounding), answer structuredness.

External parameters: v_0 — continuously incoming new texts and queries; μ_s — data complexity limit beyond which the model starts "hallucinating"; μ_k — computational cost (FLOPs) per pass.

12.2 Empirical Confirmations

RLHF and RLVR as implementation of Theorem 2. Reinforcement Learning from Human Feedback (RLHF) and Reinforcement Learning with Verifiable Rewards (RLVR, 2025) keep g and k within bounds, preventing them from falling to zero or skyrocketing [6].

Exponential acceleration (Theorem 5). According to a METR study (2025), "models double their capabilities every 7 months" [7]. This is a direct consequence of $\tau_{n+1} \approx \tau_n/2$.

MMLU-Pro as a measure of consolidation. GPT-4 achieves $\approx 88.7\%$ on MMLU, but only $\approx 72.6\%$ on the more challenging MMLU-Pro, demonstrating the measurability of k [8].

13 Application to Economic Systems: Distribution of Income and Wealth

13.1 Interpretation of Parameters

- m — accumulated capital;
- g — innovativeness, entrepreneurial activity;
- k — institutional rigidity, regulation.

13.2 Pareto Distribution as a Special Case of Theorem 6

Research by Thomas Piketty and Emmanuel Saez (2015) shows that income distribution in the upper tail follows a Pareto distribution [9]:

$$S(x) = \left(\frac{x}{\sigma}\right)^{-\alpha}, \quad x \geq \sigma \tag{21}$$

The Pareto index α for different countries and periods:

- USA (2010s): $\alpha \approx 1.5$ (high inequality)
- France (2010s): $\alpha \approx 1.8$ (moderate inequality)
- Scandinavian countries: $\alpha \approx 2.0 - 2.2$ (low inequality)

Within the framework of Theorem 6, α plays the role of inverse temperature: the smaller α, the "heavier" the tail of the distribution and the greater the share of wealth concentrated among the super-rich.

14 Application to Social Systems: Zipf's Rule and Lotka's Law

14.1 Zipf's Rule for Cities

Zipf's law (rank-size) states that the size of a city is inversely proportional to its rank [10]:

$$\text{Size} \propto \text{Rank}^{-\zeta}, \quad \zeta \approx 1 \tag{22}$$

14.2 Lotka's Law for Scientific Productivity

Alfred Lotka (1926) discovered that the number of scientists publishing n papers is inversely proportional to n^2 [11]:

$$f(n) \propto n^{-2} \tag{23}$$

This is another example of a power-law distribution, a special case of formula (19).

15 Comparative Analysis and Universality of the Model

Table 1: Interpretation of Model Parameters in Different Systems

System	**Resource** m	**Variability** g	**Consolidation** k
Physical (stick-slip)	Mass	Variability	Stiffness
Biological (DNA)	Genome integrity	Mutation potential, conformational flexibility, allele diversity	Structural rigidity, degree of chromatin packaging, association with histones
Technological (LLM)	Parameter count, training corpus size	Creativity ("temperature"), few-shot learning capability, breadth of solvable tasks	Logical rigor, factual grounding, answer structuredness, instruction-following accuracy
Economic	Accumulated capital	Innovativeness, entrepreneurial activity, new technology adoption rate	Institutional rigidity, regulatory framework, entry barriers, patent protection strength
Social	Population size	Cultural diversity, linguistic variability, social mobility	Social norms, traditions, legal institutions, level of social trust

Table 2: Empirical Confirmations of Theorems

Theorem	Confirmation	Source
Theorem 2 (feedback)	Gengram: +16.1% AUC	[3]
Theorem 5 (explosion cascade)	Doubling of LLM capabilities every 7 months	[7]
Theorem 6 (Planck spectrum)	Pareto, Zipf, Lotka distributions	[9–11]
Theorem 6 (Planck spectrum)	Token distribution in GROVER	[1]

16 Conclusion

16.1 Scientific Results

- An isomorphism between the stick-slip oscillator and a universal model of dissipative metabolism is established.
- A closed system of dynamic equations for m, g, k (10) is derived.
- The concept of a quantum of metabolic power P is introduced.
- Theorem 1 on inevitable demise with fixed α is proven.
- Theorem 2 on the survival criterion through negative feedback (12) is proven.
- Theorem 3 on the irreversibility threshold (14) is proven.
- A typology of regimes based on quantum statistics is constructed.
- Theorem 4 on the necessity of phase transitions is proven.
- Theorem 5 on the cascade of evolutionary explosions and its exponential acceleration is proven.
- Theorem 6 on the spectral power density is proven; a mathematical isomorphism with Planck's formula (20) is established.
- A comparative analysis of the theory's applications to DNA, LLMs, economics, and sociology is conducted, drawing on recent data from 2024–2026.

16.2 Worldview Implications

- **Dissipation is a resource, not a loss.** The energy dissipated by a system is a source of its development if reinvested correctly.

- **Fixed strategies are lethal.** Any system following rigid rules without adaptation is doomed.
- **Survival is homeostasis.** Maintaining g and k within certain limits is the only way for long-term existence.
- **The irreversibility threshold is measurable.** There exists a critical fraction of degraded elements beyond which collapse is inevitable.
- **Neither creativity without order, nor order without creativity.** A balance of g and k is necessary.
- **Explosion begets explosion.** Each evolutionary leap creates conditions for the next, accelerating progress.
- **The power quantum determines the pace of evolution.** The speed of a system's development is set by the amount of available power.
- **The spectrum of a dissipative system obeys Bose-Einstein statistics.** This points to a deep unity of thermodynamics, information theory, and complex systems.

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Conflict of Interest

The author declares no conflict of interest.

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