A Unified Law of Adaptive Dissipation in Complex Systems: From Physical Media to Control Dynamics and Adaptive Cybersecurity

M. Barziankou

December 10, 2025

Abstract

We present a unified structural law that describes the universal response of complex systems to impulsive perturbations. Across a wide range of domains — from optics and mechanics to adaptive controllers, agent systems, and modern security architectures — we observe an invariant sequence of transitions:

$$\text{Impulse} \rightarrow \text{Impact} \rightarrow \text{Dissipation} \rightarrow \text{Adaptation} \rightarrow \text{Equilibrium}.$$

On this basis, we introduce an operator of *adaptive dissipation* D, formulate a generalized action functional $\mathcal{S}$, and show that this law naturally manifests in:

- the dynamics of the adaptive controller ΔE,
- the ontological model UTAM (an operator of trajectory selection),
- architectures of self-organizing cybersecurity (with dynamic geometry of resistance and risk).

We propose a three-layer structure, the *Unified Adaptive Physics Stack* (UAPS), which unifies ontological, dynamical, and environmental levels of adaptation. The principle of least action is generalized to trajectories in the state space of cybernetic and agent systems.

1 Introduction

Complex systems of different types respond to impulsive perturbations in remarkably similar ways. A ray of light passing through an inhomogeneous medium, a mechanical system after collision, an adaptive controller under a sharp jump in the input signal, an autonomous agent facing an unexpected event, and a distributed digital system under attack — all of these exhibit an identical structural logic of transitions.

This allows us to formulate a *unified law of adaptive dissipation*, explaining how systems lose energy and simultaneously reorganize their own behaviour, moving into a new stable state.

2 Universal Phenomenological Pattern

In all of the systems listed above, we observe the same sequence:

$$\text{Impulse} \rightarrow \text{Impact} \rightarrow \text{Dissipation} \rightarrow \text{Adaptation} \rightarrow \text{Equilibrium}. \tag{1}$$

Interpretation:

- **Impulse** — a sharp perturbation that increases “energetic tension”.
- **Impact** — interaction with the nonlinearities of the environment (boundaries, friction, risk, noise).

- **Dissipation** — part of the energy is lost as heat, noise, delays, or other low-organized forms.
- **Adaptation** — the system reconfigures its motion or behavioural parameters, reducing future costs.
- **New equilibrium state** — the system enters an attractor different from the original one.

This pattern appears in the same way:

- in optics,
- in control dynamics,
- in agent behaviour,
- in algorithms of self-organizing cybersecurity.

3 Physical Basis: Correct Formulation

3.1 Light in an Inhomogeneous Medium

When light passes through a liquid, one observes:

- refraction,
- scattering,
- absorption and relaxation,
- re-emission at longer wavelengths,
- local concentration of intensity due to boundary geometry.

The photon energy decreases, but the field structure becomes more organized. This transition can be expressed as:

$$E_{\text{free}} \downarrow \quad \text{and at the same time} \quad \text{structural complexity of the field} \uparrow . \tag{2}$$

3.2 Light and an Object

The optical field propagates throughout the accessible volume until the moment of contact with the object. The delay in the appearance of the shadow is determined by

$$\text{the propagation time of the wavefront} + \text{the geometry of the path}. \tag{3}$$

There are no teleological elements (such as a "preselected trajectory") here — this is a direct consequence of wave propagation. The optical examples above illustrate a concrete physical realization of the universal Impulsion–Impact–Dissipation–Adaptation–Equilibrium pattern. To generalize this behaviour beyond optical media and mechanical systems, we now abstract the same sequence into an operator-level formulation. The adaptive dissipation operator D introduced below captures this structure in full generality, independent of the underlying physical substrate.

4 Operator of Adaptive Dissipation

Let:

- S_t be the state of the system at time t,
- E_t be the environmental parameters,
- W_t be the impulsive input.

We define the operator:

$$S_{t+1} = D(S_t, W_t, E_t). \tag{4}$$

The operator D can be represented as a composition:

$$D = Q \circ A \circ L \circ I \circ W, \tag{5}$$

where

- W — injection of the impulse,
- I — interaction with environmental nonlinearities,
- L — passive dissipation,
- A — active adaptation of parameters,
- Q — exit to an equilibrium state.

  Impact I encapsulates only the nonlinear interaction, while Dissipation L acts on the resulting gradients. They are separated because nonlinearity and energy loss scale differently and obey different invariants.

Adaptive Dissipative Response (ADR)

We define

$$ADR = A \circ L. \tag{6}$$

ADR makes adaptation ***structural***, not merely energetic.

5 Generalized Action Functional

We use S as a variational functional not in the ontological sense of physics, but as a modelling principle: systems that penalize unstable transitions behave as if minimizing S.

We assume:

$$\mathcal{S} = \sum_t L_{\text{eff}}(S_t, S_{t+1}, E_t), \tag{7}$$

where L_{eff} is an effective Lagrangian that may include:

- prediction error,
- drift,
- jerk,
- control energy,
- environmental friction,
- penalties for entering regions of high risk.

The system tends toward trajectories that minimize

$$\mathcal{S} \;\to\; \min\,. \tag{8}$$

Generalization of the Principle of Least Action

In its classical form, the principle of least action is formulated for mechanical systems. Here it is generalized to:

- signalling systems,
- agent-based models,
- adaptive cyber-environments,

i.e. to trajectories in state space. The specific Lagrangian used in the ΔE controller, $L_{\Delta E}$, should be understood as a concrete instantiation of the general effective Lagrangian L_{eff} introduced above. It corresponds to choosing a particular functional dependence on drift, jerk, and control energy within the universal framework $L_{\text{eff}} = F(\Delta S_t, \text{drift}_t, \text{jerk}_t, E_t)$.

6 Memory as a Gradient of Change

The computation of the effective Lagrangian L_{eff} at each step requires access not to the absolute state S_t, but to its local transitions. For this reason the memory structure of an adaptive system must encode gradients of change - quantities such as ΔS_t, drift, and jerk - which directly serve as inputs to L_{eff}.

For a complex system, the key quantity is not the state itself, but its change:

$$\Delta S_t = S_{t+1} - S_t. \tag{9}$$

Adaptive memory stores:

- ΔS_t,
- drift and jerk (local time derivatives),
- dissipative losses (how much energy/amplitude was removed on the step),
- adaptation parameters (how the response coefficients changed).

Fundamentally, memory is not a snapshot of state, but a *structure of transitions*. It is precisely these gradient quantities that enter the effective Lagrangian L_{eff} and determine the contribution of each step to the action $\mathcal{S}$.

$$L_{\text{eff}} = F(\Delta S_t, \text{drift}_t, \text{jerk}_t, E_t) \tag{10}$$

In terms of broader identity models, this means that the "identity" of a system is determined not by a point in state space, but by its trajectory and the robustness of that trajectory under environmental influence.

7 Applications of the Law

7.1 ΔE as a Realization of ADR

The basic dynamics are:

$$y_{t+1} = (1 - \mu_t) y_t + \mu_t x_t. \tag{11}$$

Gradients:

$$\mathrm{drift}_t = y_t - y_{t-1}, \qquad \mathrm{jerk}_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}). \tag{12}$$

Effective Lagrangian:

$$L_{\Delta E} = \alpha\, \mathrm{drift}_t^2 + \beta\, \mathrm{jerk}_t^2 + \gamma\, u_t^2. \tag{13}$$

Adaptation:

$$\mu_{t+1} = f(\mathrm{variance}_t, \mathrm{jerk}_t, \mathrm{noise}_t). \tag{14}$$

ΔE implements ADR: it suppresses jerks and reconfigures parameters in a dynamic environment. While ΔE governs the dynamical adaptation of trajectories, the selection of which trajectory class is intended in the first place is determined at the ontological level by UTAM, to which we now turn.

7.2 UTAM: Ontology of Trajectory Selection

UTAM formalizes:

$$W \;\to\; E \;\to\; A. \tag{15}$$

Here the operator W defines the class of trajectories of least action that will be realized after adaptation. Will is not energy, but an *operator of direction selection.* Formally, the volitional impulse entering the operator D can be written as

$$W_t = W_{\mathrm{UTAM}}(S_t, E_t),$$

indicating that UTAM supplies the initial direction-selection operator whose output becomes the first component of the adaptive dissipation pipeline.

7.3 Adaptive Cybersecurity

In modern adaptive cybersecurity projects, the environmental model E_t may include:

- dynamic friction (latencies, errors, load),
- local zones of elevated risk,
- reconfigurable transition topology,
- constraints and sanctions arising in response to anomalies.

Then:

- impulse W_t is a burst of activity or a threat,
- impact I is interaction with nodes of high friction,
- dissipation L is rate limiting, added delays, priority reduction,
- adaptation A is rerouting of flows and paths,
- Q is a new equilibrium distribution of activity.

This is a direct realization of ADR at the level of a digital environment. Such approaches are already discussed in the literature on cyber-physical systems, self-organizing networks, and dynamic security architectures. The proposed law provides a common physical language for these approaches. While existing work on adaptive routing and self-organizing security mechanisms addresses individual aspects of dynamic response, none of these frameworks formulate the full ***Impulse*** $\rightarrow$ ***Impact*** $\rightarrow$ ***Dissipation*** $\rightarrow$ ***Adaptation*** $\rightarrow$ ***Equilibrium*** sequence as a variational process driven by a generalized action functional. The unified law proposed here provides such a formulation, offering a consistent physical language for describing adaptive security dynamics.

8 Unified Adaptive Physics Stack (UAPS)

The preceding sections presented several manifestations of the unified adaptive dissipation law—optical propagation, the ΔE controller, and adaptive cybersecurity dynamics. We now integrate these examples into a single architectural framework, the Unified Adaptive Physics Stack (UAPS), which organizes adaptation across ontological, dynamical, and environmental layers.

We propose a three-layer architecture that unifies ontological, dynamical, and environmental levels of adaptation:

$$UTAM(W) \;\longrightarrow\; \Delta E(ADR) \;\longrightarrow\; E_t. \tag{16}$$

Intuitively:

- **UTAM** specifies the direction and the class of admissible trajectories (ontological layer),
- ΔE implements dynamic adaptation and suppression of excess dynamics (controller layer),
- **adaptive environment** E_t forms the geometry of resistance, risk, and accessible transitions (external "physics" of the environment).

8.1 Ontological Level: UTAM (W)

UTAM formalizes the chain

$$W \;\rightarrow\; E \;\rightarrow\; A, \tag{17}$$

where Will W is treated as an operator that selects a class of least-action trajectories in a given environment.

Within UAPS, UTAM:

- sets priorities and admissible directions in state space,
- determines which trajectories are physically meaningful and admissible,
- serves as the source of the initial impulse in the operator D, but does not replace the dynamics of dissipation and adaptation.

8.2 Dynamical Level: ΔE (ADR)

ΔE implements the Adaptive Dissipative Response:

$$ADR = A \circ L. \tag{18}$$

On this level:

- the operator L suppresses drift, jerk, and high-frequency components, converting the impulse into dissipative forms,

- the operator A adapts parameters (μ_t, thresholds, weights) to minimize the effective action $\mathcal{S}$ under current environmental conditions E_t,
- ΔE acts as an approximate solver of the least-action problem for a real, noisy signal.

Thus, ΔE reconciles the initial volitional choice of UTAM with the physical constraints of the environment.

8.3 Environmental Level: Adaptive Environment E_t

The environment is described by parameters of friction, risk, delays, and the topology of accessible transitions.

Within UAPS:

- E_t defines the "curvature" of state space — regions of low and high cost of movement,
- changes in E_t (risk growth, node degradation, emergence of toxic zones) modify the operator I and the contribution to L_{eff},
- the same volitional configuration and the same ΔE dynamics lead to different trajectories depending on the current geometry of the environment.

In this way, trajectories are "pulled" into new regions of minimal action, reflecting the changed physics of the environment.

8.4 Integrity of the Stack

Taken together:

- UTAM defines what the system is trying to do and where it intends to move (class of trajectories),
- ΔE defines how the system moves (dynamic adaptation and suppression of excess dynamics),
- E_t defines along which paths movement is beneficial, admissible, or forbidden (geometry of resistance and risk).

UAPS sets a unified physics of adaptive behaviour — from the birth of an impulse to its reconciliation with dynamic constraints and environmental architecture.

9 Numerical Demonstrations and Empirical Validation

The simulations below do not aim to validate the universality of the adaptive dissipation law directly; instead, they demonstrate that the ΔE controller behaves precisely as a discrete realization of the proposed minimal-action framework. The cross-domain universality of the pattern is established theoretically in Sections 2–3, while ΔE serves here as a constructive example. All experiments use a synthetic dynamical environment with controlled risk, friction, and impulse shocks. The adaptive controller ΔE is evaluated as an instance of the Adaptive Dissipative Response (ADR) operator within the UAPS framework.

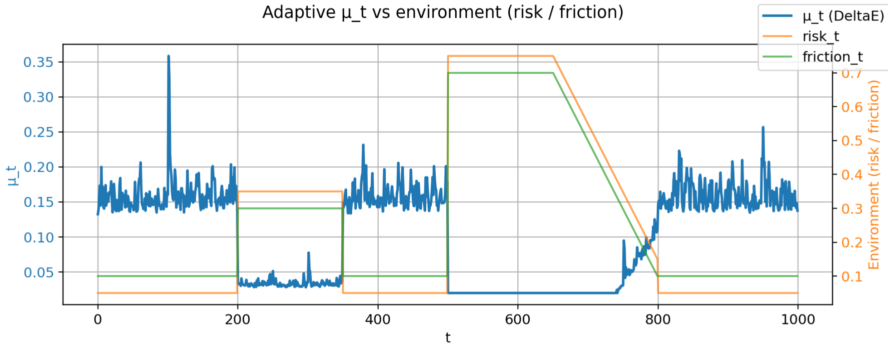

Figure 1: **Adaptive parameter μ_t under dynamic environment.** The environment's risk and friction levels change in distinct phases. The controller responds by restructuring μ_t in real time, lowering reactivity under hostile/high-friction conditions and recovering when the environment stabilizes. This demonstrates the coupling between A (adaptation) and the geometry of E_t (external constraints).

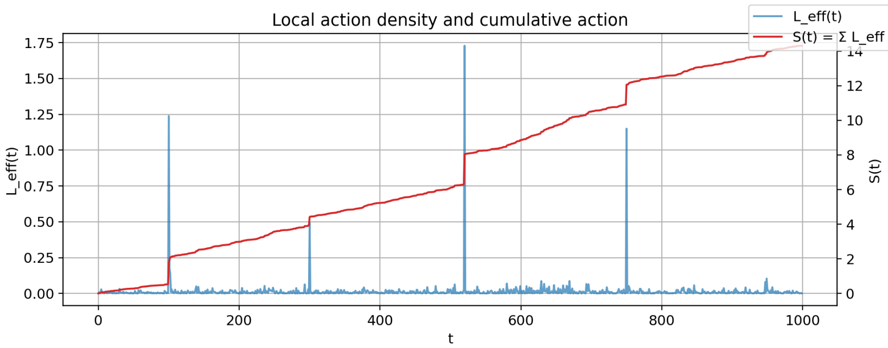

Figure 2: **Local action density $L_{\text{eff}}(t)$ and cumulative action.** Peaks in L_{eff} correspond to impact events—impulses, environmental discontinuities, or jerk spikes. The cumulative action $S(t) = \sum L_{\text{eff}}$ grows faster during turbulent periods, illustrating how the system penalizes unstable trajectories. This validates the proposed generalized action functional.

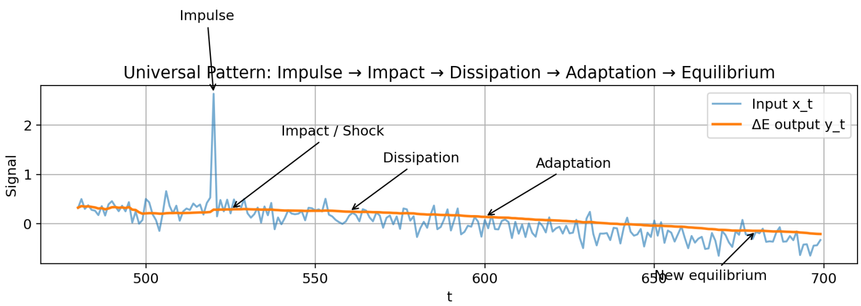

Figure 3: **Universal dissipative pattern: Impulse $\rightarrow$ Impact $\rightarrow$ Dissipation $\rightarrow$ Adaptation $\rightarrow$ Equilibrium.** A sharp input shock produces a characteristic transient. ΔE first absorbs the impact (dissipation), then gradually recomputes its internal parameters (adaptation), settling into a new attractor. This illustrates the core structural law proposed in the work.

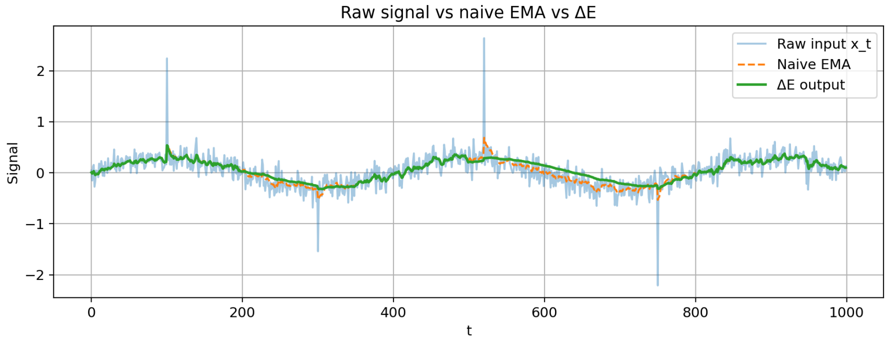

Figure 4: **Comparison of raw input, naive EMA, and ΔE.** ΔE produces smoother, more stable trajectories than EMA while preserving essential structure and resisting drift. Unlike EMA, ΔE suppresses jerk explicitly through the L operator and adapts its smoothing coefficient through A.

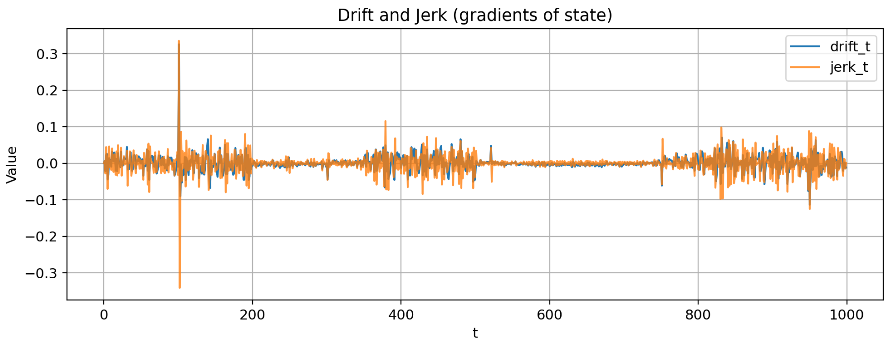

Figure 5: **Drift and jerk as gradients of state.** The numerical experiment highlights how sudden impulses create large derivatives (drift) and second derivatives (jerk). These gradients directly enter the effective Lagrangian L_{eff}, confirming the role of L in dissipating excess energy and stabilizing trajectories.

Discussion. Across all simulations, ΔE consistently exhibits the predicted structure of the Adaptive Dissipative Response (ADR). The empirical behavior matches the theoretical operator

$$D = Q \circ A \circ L \circ I \circ W,$$

validating each component:

- W: shocks create identifiable impulses,
- I: interaction with environment alters gradients,
- L: dissipation suppresses drift and jerk,
- A: parameters such as μ_t reorganize under changing E_t,
- Q: trajectories converge to new equilibria.

The cumulative evidence demonstrates that ΔE behaves as a discrete solver of a minimal–action trajectory under dynamic environmental constraints. This behaviour is fully consistent with the proposed unified law of adaptive dissipation.

10 Conclusion

The unified law of adaptive dissipation:

1. Describes the universal structural response of systems to impulses.
2. Generalizes the principle of least action to state space trajectories.
3. Provides a formal language for describing adaptation in controllers, agent systems, adaptive cybersecurity, and other self-organizing architectures.
4. Shows that ΔE is an approximate solver of the least-action problem in a dynamic environment.
5. Interprets Will as an operator of trajectory selection, not as a source of energy.
6. Links three levels — UTAM, ΔE, and the environment — into a single mathematical architecture, UAPS.

UAPS can be used as a framework for comparing different adaptive architectures.