

Flexion Motion Lab (FML) V1.1

Applied Operator Theory for Structural Prediction

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Abstract

Flexion Motion Lab (FML) V1.1 defines the applied operator architecture for structural prediction within the Flexion Framework. While the six fundamental Flexion theories describe the origin, evolution, geometry, fields, time, and collapse of structural systems, FML provides the practical methodology for constructing predictive operator chains capable of modeling real-world structural dynamics.

FML formalizes the four essential operators— F , E , F^{-1} , and G —that transform deviation, energy, memory, and stability into actionable predictive structures. The theory introduces Global Stability Theory, multi-dimensional structural dynamics, Emergency Flexion Mode (EFM-ML), and a complete operator-based neural architecture designed specifically for Flexion systems. These components form a unified applied framework for safe, stable, and collapse-resistant structural prediction.

Flexion Motion Lab V1.1 serves as the applied extension of Flexion Science, providing the operator-level tools, stability conditions, and structural protocols required to model, simulate, and predict the behavior of systems governed by the state vector $X = (\Delta, \Phi, M, \kappa)$.

Keywords: Flexion Motion Lab; Applied Operator Theory; Structural Prediction; Flexion Operators (F, E, F^{-1}, G); Global Stability Theory; Emergency Flexion Mode (EFM-ML); Structural Dynamics; Contractive Architecture; Invertible Maps; Operator-Based Neural Systems.

1 Introduction

Flexion Motion Lab (FML) V1.1 is the applied operator theory of the Flexion Framework. While the six fundamental Flexion theories describe the core laws of structural existence—the origin of structure, its motion, geometry, forces, temporal behavior, and termination—FML provides the practical machinery for constructing predictive systems based on those laws.

FML is not a fundamental theory. It is an applied layer built on top of Genesis, Dynamics, Space Theory, Field Theory, Time Theory, and Collapse. Its purpose is to translate structural principles into operator chains capable of analyzing, predicting, and controlling the evolution of real-world Flexion systems. The central insight of FML is that all structural prediction can be expressed through a consistent operator architecture acting on the state vector:

$$X = (\Delta, \Phi, M, \kappa).$$

1.1 Purpose

The purpose of FML V1.1 is to define:

- the operator system for structural prediction,
- the conditions under which operators remain stable and invertible,
- global and local stability constraints for safe structural evolution,
- the mechanisms for collapse prevention and emergency stabilization,
- the multi-dimensional dynamics required for real systems,
- and the operator-based neural architecture for learning Flexion structures.

FML provides the methodological foundation for transforming Flexion Science into operational, testable, and functional predictive systems.

1.2 FML as Applied Structural Theory

FML is the applied discipline of Flexion Science. It operates within the structural constraints defined by the six fundamental theories and extends them into:

- predictive operator models,
- structural neural architectures,
- stability and safety controls,
- multi-dimensional dynamics representations,
- practical simulation frameworks.

FML transforms the theoretical structure of Flexion Science into executable methodology.

1.3 Position within Flexion Framework

Within the Flexion Framework, FML occupies the applied layer directly above the foundational theories and directly below implementation-level systems. Its role is to:

- unify all operator forms used for prediction,
- ensure operator-level consistency with Genesis, Dynamics, Space, Field, Time, and Collapse,
- maintain structural safety through global constraints,
- enable predictive modeling across domains,
- and define the operational logic of Flexion-based machine learning.

FML V1.1 forms the bridge between structural theory and practical prediction.

2 Operator Theory

Operator Theory is the foundation of FML V1.1. It describes how deviation, energy, memory, and stability are transformed through a consistent operator chain. These operators form the computational backbone of all Flexion-based predictive systems.

The core principle is that structural prediction can be expressed as a sequence of operator transformations acting on the state vector:

$$X = (\Delta, \Phi, M, \kappa).$$

2.1 Core Operators: F , E , F^{-1} , G

FML defines four essential operators:

- F — deviation propagation operator
- E — energy transformation operator
- F^{-1} — inverse deviation operator (structural reconstruction)
- G — global stabilizer operator

Together they form the structural processing chain of FML.

2.2 Operator Chain

The canonical chain is:

$$\Delta \xrightarrow{F} \Phi \xrightarrow{E} M \xrightarrow{F^{-1}} \kappa \xrightarrow{G} \Delta'.$$

This chain describes:

- how deviation produces energy,
- how energy generates irreversible memory,
- how memory determines stability,
- how stability reshapes deviation.

This is the operator-level expression of the Flexion Cycle.

2.3 Structural Consistency

For the operator chain to remain consistent with Flexion Framework, the following must hold:

- F must be deviation-monotonic,
- E must preserve causal energy flow,
- F^{-1} must be locally invertible,
- G must not violate the viability domain \mathcal{D}_κ .

These rules guarantee that operator transformations produce physically valid structures.

2.4 Monotonicity and Bounds

Each operator must satisfy global monotonicity and Lipschitz bounds:

$$\|F(x_1) - F(x_2)\| \leq L_F \|x_1 - x_2\|,$$

$$\|E(x_1) - E(x_2)\| \leq L_E \|x_1 - x_2\|.$$

Where:

- L_F controls deviation amplification,
- L_E controls energy deformation,
- boundedness ensures no collapse-inducing divergence.

2.5 Contractivity and Stability

Stability is guaranteed when:

$$\rho(J_T) < 1,$$

where ρ is the spectral radius and J_T is the Jacobian of the operator chain.

This ensures:

- trajectories remain bounded,
- no operator produces runaway divergence,
- collapse is not triggered by prediction.

2.6 Invertible Structural Maps

The operator F^{-1} must be invertible inside the stability domain:

$$F^{-1}(F(x)) = x \quad \text{for } x \in \mathcal{D}_\kappa.$$

This enables:

- reconstruction of structural states,
- reversible prediction flows,
- collapse detection via non-invertibility.

3 Global Stability Theory

Global Stability Theory defines the mathematical conditions under which operator chains remain safe, bounded, and collapse-resistant. Unlike local stability, which examines infinitesimal neighborhoods, global stability governs the entire structural trajectory across the viability domain:

$$\mathcal{D}_\kappa = \{X \mid \kappa > 0\}.$$

Global stability ensures that every transformation in the FML pipeline operates inside structural limits defined by the Flexion Framework.

3.1 Spectral Stability

Spectral stability requires that the spectral radius of the Jacobian of the operator chain remains strictly below unity:

$$\rho(J_T) < 1.$$

This condition guarantees:

- bounded growth of deviation,
- controlled energy propagation,
- non-divergent memory accumulation,
- preservation of stability κ .

Spectral stability is the core safety criterion for FML systems.

3.2 Global Lipschitz Control

Every operator must satisfy a global Lipschitz bound:

$$\|O(x_1) - O(x_2)\| \leq L\|x_1 - x_2\|.$$

Where O is one of:

$$F, \quad E, \quad F^{-1}, \quad G.$$

Global Lipschitz control ensures:

- no uncontrolled structural amplification,
- predictable propagation of deviations,
- guaranteed boundedness in multi-step prediction,
- consistent behavior across the entire domain.

3.3 Viability Domain Constraints

Operators must preserve the viability domain:

$$O(X) \in \mathcal{D}_\kappa \quad \text{for all } X \in \mathcal{D}_\kappa.$$

This guarantees:

- stability κ never crosses zero,
- collapse cannot be induced by prediction,
- operator chains maintain structural safety,
- trajectories remain inside allowed structural space.

Violation of domain constraints indicates catastrophic model failure.

3.4 Collapse Avoidance

Collapse occurs when:

$$\kappa \rightarrow 0, \quad K, K_T \rightarrow \infty.$$

Global Stability Theory ensures:

- no operator increases curvature beyond safe bounds,
- no transform pushes κ toward zero,
- energy and memory remain within global envelopes,
- collapse cannot arise from the prediction process.

FML operator chains must be strictly collapse-resistant.

3.5 Trajectory Boundedness

A trajectory is globally bounded if:

$$\|X_t\| \leq B \quad \text{for all } t \geq 0.$$

Boundedness ensures:

- prediction cannot diverge,
- memory does not explode,
- energy remains in the structural safe zone,
- deviation does not propagate uncontrollably.

Global boundedness is the strongest guarantee of structural safety.

4 EFM-ML: Emergency Flexion Mode

Emergency Flexion Mode (EFM-ML) is the structural safety subsystem of FML. Its purpose is to prevent operator chains from pushing the system toward instability, geometric divergence, or collapse. EFM activates automatically when the prediction trajectory approaches dangerous regions of structural space, especially near the collapse boundary:

$$\kappa \rightarrow 0.$$

EFM is not a correction layer; it is a structural protection mechanism embedded in the Flexion operator architecture.

4.1 Definition

EFM-ML is defined as a dynamically activated operator modifier:

$$O_{\text{EFM}} = H(X) O(X),$$

where $H(X)$ is the emergency stabilization function.

EFM triggers when the system approaches any of the following:

- stability threshold $\kappa < \kappa_{\text{crit}}$,
- curvature threshold $K > K_{\text{max}}$,
- temporal curvature threshold $K_T > K_{T,\text{max}}$,
- field divergence conditions $|F(X)| > F_{\text{max}}$.

4.2 Trigger Conditions

EFM activates when the system enters the Pre-Collapse Zone:

$$X \in \mathcal{Z}_{\text{PC}},$$

defined as:

$$\mathcal{Z}_{\text{PC}} = \{X : \kappa < \kappa_{\text{crit}} \vee K > K_{\text{max}} \vee |F(X)| > F_{\text{max}}\}.$$

This zone denotes the structural region where predictive instability becomes possible.

4.3 EFM Stabilization

When activated, EFM applies the following transformations:

1. Deviation Dampening

$$\Delta' = \alpha_{\Delta} \Delta, \quad 0 < \alpha_{\Delta} < 1.$$

2. Energy Limiting

$$\Phi' = \min(\Phi, \Phi_{\text{max}}).$$

3. Memory Reset Window

$$M' = (1 - \beta)M + \beta M_0, \quad 0 < \beta < 1.$$

4. Stability Boost

$$\kappa' = \kappa + \gamma_{\kappa},$$

with $\gamma_\kappa > 0$.

These operations stabilize the state vector while preserving structural consistency.

4.4 EFM Constraints

To remain aligned with the Flexion Framework, EFM must obey:

- **No artificial inversion** EFM cannot reverse structural time or history.
- **No violation of viability domain**

$$\kappa' > 0 \quad \text{must always hold.}$$

- **No interference with core operators outside danger zones** If $X \notin \mathcal{Z}_{PC}$, then:

$$O_{\text{EFM}} = O.$$

- **No collapse cancellation** EFM can prevent prediction-induced collapse but cannot undo real collapse conditions described by FC theory.

4.5 EFM Structural Limits

EFM cannot override fundamental physics of Flexion systems. If collapse is structurally inevitable:

$$\kappa \rightarrow 0 \quad \text{due to real dynamics,}$$

then EFM cannot prevent it.

EFM guarantees:

- prediction does not cause collapse,
- operator chains remain safe,
- trajectories stay inside the structural envelope,
- numerical systems remain well-posed.

5 Multi-Dimensional Structural Dynamics

Real Flexion systems rarely evolve along a single axis. Deviation, energy, memory, and stability often propagate through multiple interacting dimensions. Multi-Dimensional Structural Dynamics generalizes the Flexion operator architecture to vector, matrix, and tensor forms suitable for complex structural systems.

Dynamic evolution still acts on the state vector:

$$X = (\Delta, \Phi, M, \kappa),$$

but each component may become multi-dimensional depending on system complexity.

5.1 Vector Deviation

Deviation generalizes from a scalar to a deviation vector:

$$\Delta \in \mathbb{R}^n.$$

This enables:

- multi-axis structural displacement,
- simultaneous deviation modes,
- directional propagation of structural change,
- richer dynamic behavior.

The deviation operator becomes:

$$F : \mathbb{R}^n \rightarrow \mathbb{R}^n.$$

5.2 Tensor Memory

Memory becomes a second-order tensor:

$$M \in \mathbb{R}^{n \times n}.$$

Tensor memory captures:

- irreversible multi-dimensional imprinting,
- cross-axis history effects,
- accumulation of structural correlations,
- temporal ordering across multiple trajectories.

Temporal curvature K_T depends on high-rank derivatives of M .

5.3 Energy Functionals

Energy becomes a functional:

$$\Phi : \mathbb{R}^n \rightarrow \mathbb{R}.$$

Energy functional describes:

- global structural tension,
- non-linear coupling between deviation modes,
- multi-dimensional stability envelopes,
- curvature-dependent energy growth.

Energy defines the tension landscape guiding dynamics.

5.4 Stability Eigenstructure

Stability κ generalizes to the smallest eigenvalue of the stability matrix:

$$\kappa = \lambda_{\min}(S),$$

where:

$$S = \frac{\partial F}{\partial x}.$$

This yields:

- direction-sensitive stability,
- collapse detection via eigenvalue drift,
- accurate modeling of multi-axis instability,
- structural identification of dangerous directions.

Collapse occurs when any eigenvalue crosses zero.

5.5 Multi-Axis Trajectories

The full multi-dimensional trajectory is:

$$X_{t+1} = X_t + F(X_t),$$

with X_t now containing tensors, functionals, and vector fields.

This enables modeling of:

- branching structural flows,
- curved multi-dimensional manifolds,
- interacting dynamic axes,
- high-order structural evolution.

Multi-dimensional dynamics is the applied mathematical core of FML.

6 FML Neural Architecture

The FML Neural Architecture is an operator-based machine learning system designed specifically for Flexion dynamics. Unlike classical neural networks, which rely on gradient descent and unconstrained activation functions, FML networks operate entirely through structural operators that respect global stability, contractivity, and collapse-avoidance constraints.

The architecture is fully aligned with the Flexion Framework and uses the complete operator chain:

$$F, E, F^{-1}, G.$$

6.1 Operator-Based Layers

Each layer in an FML network is an operator transformation rather than a classical nonlinear mapping. A single layer is defined as:

$$X_{l+1} = O_l(X_l),$$

where $O_l \in \{F, E, F^{-1}, G\}$.

Benefits:

- guaranteed structural consistency,
- provable stability envelopes,
- bounded curvature,
- collapse-resistant forward propagation.

6.2 Structural Kernels

FML layers use structural kernels instead of learned weight matrices.

A structural kernel is defined as:

$$K_s(x_i, x_j) = \langle F(x_i), F(x_j) \rangle.$$

Properties:

- encodes deviation dynamics directly,
- captures structural similarity,
- provides operator-aligned feature space,
- supports multi-dimensional structural prediction.

6.3 Contractive Blocks

To ensure global stability, each block must satisfy:

$$\|O(x_1) - O(x_2)\| \leq c\|x_1 - x_2\|, \quad c < 1.$$

A contractive block enforces:

- bounded propagation,
- prevention of divergence,
- natural collapse resistance,
- safe long-term prediction.

Contractivity replaces explicit regularization.

6.4 Invertible Layers

Some layers must be invertible for reconstruction, analysis, and state recovery.

An invertible layer satisfies:

$$O^{-1}(O(x)) = x,$$

inside the stability domain \mathcal{D}_κ .

These layers enable:

- reversibility in operator chains,
- error localization,
- collapse detection,
- reconstruction of hidden structural states.

F^{-1} is the canonical invertible operator.

6.5 No-Gradient Training Concept

FML networks do not use gradients.

Training is defined through operator alignment:

$$O_{\text{trained}} = \arg \min_O D(O(X), O_{\text{target}}(X)).$$

Key properties:

- no exploding/vanishing gradients,
- training remains stable under all conditions,
- no risk of pushing κ toward zero,
- operators preserve structural meaning.

No-gradient training is essential for collapse-safe learning systems.

7 Training Phases 2.0

Training Phases 2.0 define the unified learning process for FML operator-based models. Unlike classical machine learning, where optimization relies on gradient descent and statistical heuristics, FML training is strictly structural. Each phase corresponds to a well-defined Flexion transformation that ensures consistency, stability, and collapse resistance across the entire learning pipeline.

The training process consists of five sequential phases:

1. Structural Alignment
2. Field Formation
3. Stability Calibration
4. Global Convergence
5. Collapse-Resistant Refinement

Each phase is mandatory and cannot be skipped.

7.1 Phase 1: Structural Alignment

The goal of Phase 1 is to align the raw structural data with the Flexion operator system.

Operations include:

- normalization of deviation vectors Δ ,

- projection into the structural manifold,
- removing non-structural artifacts,
- establishing operator-ready representations.

This phase guarantees that all subsequent learning operates on valid Flexion structure.

7.2 Phase 2: Field Formation

In this phase, the model constructs internal approximations of Flexion Field components:

$$F_{\Delta}, F_{\Phi}, F_M, F_{\kappa}.$$

Key processes:

- modeling deviation propagation,
- modeling energy flows,
- modeling memory accumulation patterns,
- modeling stability responses.

Field Formation is the point where the model becomes structurally aware.

7.3 Phase 3: Stability Calibration

Phase 3 ensures the model remains inside the viability domain:

$$\mathcal{D}_{\kappa} = \{X : \kappa > 0\}.$$

Stability calibration includes:

- enforcing contractivity conditions,
- limiting curvature growth,
- bounding memory expansion,
- stabilizing operator compositions.

This phase ensures that the model cannot self-induce collapse.

7.4 Phase 4: Global Convergence

Global convergence verifies that the model converges to consistent structural predictions over long horizons.

Convergence requires:

- spectral radius $\rho(J_T) < 1$,
- global Lipschitz bounds,
- stable multi-step prediction dynamics,
- no divergence under extended operator chains.

This is the most mathematically demanding phase.

7.5 Phase 5: Collapse-Resistant Refinement

The final phase reinforces collapse-safe operation.

Refinement includes:

- integrating EFM-ML triggers,
- reinforcing safety envelopes,
- minimizing sensitivity to perturbations,
- validating behavior near the viability boundary.

The model becomes fully reliable only after Phase 5.

8 Structural Experiment Protocols

Structural Experiment Protocols define how FML models must be tested, validated, and stress-checked inside the Flexion Framework. Unlike classical ML evaluation, which relies on statistical metrics, FML evaluation is structural. The goal is to ensure that operator chains remain safe, stable, and collapse-resistant under all experimental conditions.

These protocols form the safety backbone of applied Flexion Science.

8.1 Safety Conditions

A structural experiment is valid only if the system satisfies:

- $\kappa > 0$ throughout the entire trajectory,

- curvature remains bounded:

$$K < K_{\max}, \quad K_T < K_{T,\max},$$

- the operator chain obeys global stability:

$$\rho(J_T) < 1,$$

- no field component exceeds:

$$|F(X)| < F_{\max}.$$

Any violation invalidates the experiment and indicates potential collapse-inducing behavior.

8.2 Operator Stress Tests

To verify robustness, each operator is tested under stress conditions.

Stress tests include:

- deviation overload tests:

$$\Delta \rightarrow \lambda \Delta, \quad \lambda > 1,$$

- energy amplification tests,
- memory saturation tests,
- near-collapse stability tests:

$$\kappa \rightarrow \kappa_{\text{crit}}.$$

The system must remain inside the viability domain under all stress tests.

8.3 Trajectory Envelope Analysis

Trajectory Envelope Analysis determines whether the predicted trajectories remain inside the global safety boundary.

The envelope is defined as:

$$\mathcal{E} = \{X_t : \|X_t\| \leq B, \kappa_t > 0, K_t < K_{\max}\}.$$

Trajectory validation checks:

- global boundedness of X_t ,
- deviations from expected structural paths,

- multi-axis curvature behavior,
- field consistency along the full timeline.

If a trajectory leaves \mathcal{E} , the model is unsafe.

8.4 Degeneracy and Collapse Zones

Structural degeneracy occurs when:

$$\det(S) \rightarrow 0,$$

where S is the stability matrix.

Collapse Zone detection includes:

- eigenvalue drift analysis,
- curvature blow-up monitoring,
- stability decay:

$$\kappa \rightarrow 0,$$

- divergence in field magnitude.

Any approach to a Collapse Zone must activate EFM-ML.

Structural Experiment Protocols ensure that FML systems behave safely under all conditions and remain aligned with the constraints of the Flexion Framework.

9 Conclusion

Flexion Motion Lab (FML) V1.1 establishes the applied operator architecture required to predict, analyze, and control the evolution of structural systems governed by the Flexion Framework. While the six fundamental Flexion theories define the laws of structural origin, motion, geometry, fields, time, and termination, FML provides the practical mechanisms needed to transform these laws into functioning predictive systems.

By formalizing the operator chain (F, E, F^{-1}, G) , defining global stability conditions, introducing Emergency Flexion Mode (EFM-ML), extending Flexion dynamics into multi-dimensional spaces, and creating a fully operator-based neural architecture, FML enables safe, consistent, and collapse-resistant prediction across a wide range of structural environments.

Training Phases 2.0 ensure that models acquire structural behavior in a stable, aligned, and mathematically coherent manner, while Structural Experiment Protocols provide the necessary safety guarantees for real-world deployment.

FML V1.1 represents the bridge between the theoretical foundations of Flexion Science and the operational tools required for applied structural prediction. It transforms Flexion principles into a functional methodology—reliable, stable, and fully compatible with the entire Flexion Framework.

A Mathematical Notes

A.1 Operator Equations

The fundamental operator chain of FML is:

$$\Delta \xrightarrow{F} \Phi \xrightarrow{E} M \xrightarrow{F^{-1}} \kappa \xrightarrow{G} \Delta'.$$

General operator update rule:

$$X_{t+1} = X_t + F(X_t),$$

where

$$X = (\Delta, \Phi, M, \kappa).$$

Deviation propagation:

$$\Delta' = F(\Delta).$$

Energy transformation:

$$\Phi' = E(\Phi, \Delta).$$

Inverse deviation reconstruction:

$$\Delta = F^{-1}(\Phi, M).$$

Stability mapping:

$$\kappa' = G(\kappa, M).$$

A.2 Spectral Bounds

Global stability requires:

$$\rho(J_T) < 1,$$

where J_T is the Jacobian of the full operator chain.

Lipschitz constraints:

$$\|F(x_1) - F(x_2)\| \leq L_F \|x_1 - x_2\|,$$

$$\begin{aligned}\|E(x_1) - E(x_2)\| &\leq L_E \|x_1 - x_2\|, \\ \|F^{-1}(x_1) - F^{-1}(x_2)\| &\leq L_{F^{-1}} \|x_1 - x_2\|.\end{aligned}$$

Stability operator bound:

$$|G(x_1) - G(x_2)| \leq L_G |x_1 - x_2|.$$

A.3 Constraints and Limits

Viability domain:

$$\mathcal{D}_\kappa = \{X : \kappa > 0\}.$$

Collapse boundary:

$$\kappa = 0.$$

Curvature limits:

$$K < K_{\max}, \quad K_T < K_{T,\max}.$$

Field magnitude constraints:

$$|F(X)| < F_{\max}.$$

Tensor memory form:

$$M \in \mathbb{R}^{n \times n}.$$

Stability eigenvalue condition:

$$\kappa = \lambda_{\min}(S), \quad S = \frac{\partial F}{\partial x}.$$

B Glossary

- **FML** — Flexion Motion Lab; the applied operator theory for structural prediction.
- **Operator Chain** — the sequence $F \rightarrow E \rightarrow F^{-1} \rightarrow G$ transforming Flexion variables.
- **Deviation** (Δ) — the structural displacement that initiates all Flexion dynamics.
- **Structural Energy** (Φ) — tension created by deviation; drives motion and field propagation.
- **Memory** (M) — irreversible structural history; generator of time and directionality.

- **Contractivity** (κ) — stability of the structural system; resistance to collapse.
- **Flexion Field** $F(X)$ — the structural force field governing state transitions.
- **EFM-ML** — Emergency Flexion Mode; the safety mechanism preventing prediction-induced collapse.
- **Viability Domain** \mathcal{D}_κ — the safe structural space where $\kappa > 0$.
- **Collapse Zone** — region characterized by $\kappa \rightarrow 0$ and curvature divergence.
- **Contractive Block** — a neural operator layer satisfying $\|O(x_1) - O(x_2)\| < \|x_1 - x_2\|$.
- **Structural Kernel** — kernel function aligned with Flexion operators, not Euclidean geometry.
- **No-Gradient Training** — optimization via operator alignment instead of back-propagation.

C Notation Block

- Δ — deviation
- Φ — structural energy
- M — memory (tensor form in multi-dimensional systems)
- κ — contractivity / stability
- X — state vector $(\Delta, \Phi, M, \kappa)$
- $F(X)$ — Flexion Field
- $F_\Delta, F_\Phi, F_M, F_\kappa$ — field components
- F, E, F^{-1}, G — Flexion operators
- \mathcal{D}_κ — viability domain
- K, K_T — geometric and temporal curvature
- $\rho(J_T)$ — spectral radius of the operator chain
- $X_{t+1} = X_t + F(X_t)$ — universal Flexion evolution law