

Strategic Imperatives for SymC Deployment: A Translational Roadmap for Optimal Control Theory in Oncology

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Version 2.0 — November 2025

Abstract

Revision Abstract Addendum: This revision clarifies that while $\chi = 1$ defines the mathematical critical-damping boundary, clinical systems perform optimally within the adaptive window $0.8 \leq \chi \leq 1.0$, where rapid suppression is balanced with feedback capacity and resistance management.

This paper outlines the translational deployment of the Symmetrical Convergence (SymC) framework within clinical oncology. Building on prior mathematical validation, this work establishes the roadmap for integrating SymC's stability ratio $\chi \equiv \gamma/(2|\omega|)$ with Optimal Control Theory (OCT) to design adaptive, personalized cancer treatment strategies. The paper introduces the CAT–OCT (Comparative Adaptive Therapy – Optimal Control Trial) protocol, which applies real-time feedback from circulating tumor DNA (ctDNA) kinetics to guide dose modulation and maintain therapeutic equilibrium. By reframing cancer management as a dynamic control system, SymC provides a predictive, mathematically grounded alternative to the conventional Maximum Tolerated Dose (MTD) paradigm. The roadmap defines the necessary clinical partnerships, data calibration strategies, and funding pathways required to move from synthetic validation to Phase II adaptive trials.

Keywords: Adaptive control; Oncology; Feedback systems; Optimal control theory; Symmetrical Convergence (SymC); ctDNA; Translational modeling; Near-critical damping; Clinical systems theory.

Classification (suggested PACS/PhySH): 87.19.xj; 87.10.Ed; 05.45.-a; 02.30.Yy.

1 Introduction

The translational deployment of the SymC framework extends the critical-damping principle from theoretical control to clinically measurable feedback systems. Previously, the stability criterion was expressed as $\chi \geq 1$, implying that maintaining critical or overdamped control

ensured stability. Subsequent analyses established that **optimal clinical adaptability occurs within the window** $0.8 \leq \chi \leq 1.0$, where the system retains rapid suppression with minimal oscillation and sufficient feedback reserve. Operating exactly at $\chi = 1$ achieves the fastest monotonic convergence but eliminates adaptive capacity; slight underdamping ($\chi \approx 0.9$) preserves information flow needed for real-time therapeutic adjustment.

2 Mechanistic modeling and stability objective

Within a two-state control template (tumor burden X , control or drug effect Y), linearization around an equilibrium yields eigenvalues $\lambda_{\pm} = -\gamma \pm i\omega$ and $\chi = \gamma/(2|\omega|)$. In this translational form, the objective is not to enforce $\chi = 1$ exactly, but to *minimize deviation from* $\chi_{\text{opt}} \approx 0.9$. This ensures responsiveness while avoiding oscillatory relapse. The stability objective for parameter estimation or controller design can be written:

$$J = [(\chi(t) - 0.9)^2] + \lambda_u[u(t)^2],$$

where $u(t)$ denotes therapeutic control input and λ_u a regularization term balancing efficacy and toxicity.

3 CAT–OCT protocol: adaptive control in practice

The CAT–OCT protocol operationalizes the adaptive window through measurable biomarkers such as ctDNA, tumor markers, or imaging-derived burden estimates. For each patient, $\chi(t)$ is estimated from recent data via envelope-decay and frequency analysis (e.g. Hilbert or Prony methods).

Operational rule set.

$$\begin{cases} \chi(t) < 0.8 : & \text{Underdamped instability. Increase control intensity or shorten interval.} \\ 0.8 \leq \chi(t) \leq 1.0 : & \text{Adaptive optimum. Maintain current regimen and monitor.} \\ 1.0 < \chi(t) \leq 1.2 : & \text{Acceptable margin. Observe for overdamping drift.} \\ \chi(t) > 1.2 : & \text{Overdamped rigidity. Taper dose to restore adaptability.} \end{cases}$$

These quantitative thresholds define the actionable guardrails for CAT–OCT dosing schedules. They preserve feedback responsiveness while minimizing relapse probability.

4 Data calibration and feedback estimation

Real-time $\chi(t)$ estimation depends on signal quality from ctDNA kinetics or related biomarkers. Measurement noise and sampling delays make exact targeting of $\chi = 1$ impractical; the chosen 0.8–1.0 window maximizes robustness to uncertainty. Under typical conditions, slight oscillatory behavior near $\chi \approx 0.9$ enhances parameter observability and improves control adaptation. The feedback estimator integrates moving-window regression and frequency tracking to provide continuous $\chi(t)$ updates.

5 Discussion and translational roadmap

This revision aligns the oncology roadmap with the updated SymC adaptive-window model. The critical-damping boundary ($\chi = 1$) remains the mathematical reference, but the practical control target ($\chi \approx 0.9$) ensures durability, flexibility, and safety. Future deployment phases include:

1. Retrospective validation of χ thresholds in clinical datasets.
2. Development of standardized biomarker pipelines for $\chi(t)$ estimation.
3. Integration of toxicity and resistance models into adaptive controllers.
4. Prospective CAT–OCT Phase II trials maintaining $0.8 \leq \chi \leq 1.0$ as the primary control criterion.

This framework preserves the quantitative rigor of SymC while grounding it in realistic, falsifiable clinical operations.

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