Analogies Between Nuclear Feedback Dynamics and Recurrent Neural Networks

Abstract

The dynamic behavior of a two-region RBMK reactor can be interpreted through the lens of recurrent neural networks (RNNs). This note demonstrates that the nonlinear feedback loops in neutron kinetics—involving delayed neutron precursors, void reactivity, and Doppler effects—mirror gated recurrent mechanisms in deep learning. We show that the reactor's Jacobian stability conditions correspond to gradient stability conditions in RNNs, and that the onset of oscillations in the core is mathematically analogous to gradient explosion phenomena.

1. Two-Region RBMK Model

Let $\phi_1(t)$ and $\phi_2(t)$ denote the neutron fluxes in the lower and upper regions of the core, respectively, and $C_i(t)$ represent the delayed neutron precursor concentration in region i. A simplified two-region model can be written as:

$$\dot{\phi}_1 = \frac{\rho_1 - \beta}{\Lambda}\phi_1 + k_{12}\phi_2 + \lambda C_1, \tag{1}$$

$$\dot{\phi}_2 = \frac{\rho_2 - \beta}{\Lambda}\phi_2 + k_{21}\phi_1 + \lambda C_2, \tag{2}$$

$$\dot{C}_i = \frac{\beta}{\Lambda}\phi_i - \lambda C_i, \quad i = 1, 2. \tag{3}$$

Here Λ is the prompt neutron generation time, β the delayed neutron fraction, and λ the decay constant of precursors.

The reactivities ρ_1 and ρ_2 are composed of additive physical feedbacks:

$$\rho_i = \rho_c + \alpha_v V_i + \alpha_T T_i,$$

where ρ_c is control-rod worth, α_v and α_T are the void and Doppler coefficients, and V_i, T_i denote void and temperature perturbations.

Positive void feedback ($\alpha_v > 0$) increases reactivity as steam forms, while negative Doppler feedback ($\alpha_T < 0$) suppresses it as fuel temperature rises.

2. Neural Network Analogy

We can interpret each flux $\phi_i(t)$ as the hidden activation h_t in a recurrent neural network:

$$h_t = f(W_h h_{t-1} + W_x x_t + b),$$

where W_h represents recurrent weights (inter-region coupling k_{ij}) and W_x the external inputs (control rod and temperature effects).

The delayed neutron precursors C_i serve as a memory variable analogous to the LSTM cell state c_t:

$$c_t = (1-\lambda)c_{t-1} + \tfrac{\beta}{\Lambda} h_{t-1},$$

providing temporal persistence across reactor time steps.

Thus the system resembles a gated recurrent unit where C_i acts as the "forget/remember" gate, and reactivity terms modulate the effective gain on h_t.

3. Linearization and Stability

Linearizing the two-region model about the steady state $(\phi_1^*, \phi_2^*, C_1^*, C_2^*)$ yields:

$$\dot{\mathbf{x}} = J\mathbf{x}, \quad \mathbf{x} = [\,\delta\phi_1,\, \delta\phi_2,\, \delta C_1,\, \delta C_2\,]^T,$$

with Jacobian

$$J = \begin{bmatrix} \dfrac{\rho_1^* - \beta}{\Lambda} & k_{12} & \lambda & 0 \\ k_{21} & \dfrac{\rho_2^* - \beta}{\Lambda} & 0 & \lambda \\ \dfrac{\beta}{\Lambda} & 0 & -\lambda & 0 \\ 0 & \dfrac{\beta}{\Lambda} & 0 & -\lambda \end{bmatrix}.$$

The eigenvalues of J determine whether flux perturbations grow or decay. A Hopf-like oscillation arises when $\Re(\lambda_{\max}(J)) = 0$.

For discrete RNN updates,

$$h_{t+1} = f(W_h h_t + W_x x_t),$$

the equivalent stability condition for gradient propagation is

$$\left| \frac{\partial h_{t+1}}{\partial h_t} \right| < 1 \quad \Longleftrightarrow \quad |\lambda_{\max}(J)| < 0,$$

showing a direct correspondence between nuclear feedback stability and vanishing/exploding gradients in RNNs.

4. Discussion

This analogy suggests that excessive positive void reactivity (α_v large) acts like a recurrent weight $W_h > 1$, leading to runaway activation analogous to gradient explosion. Conversely, strong Doppler feedback ($\alpha_T < 0$) introduces damping analogous to gradient clipping or regularization. The delayed neutron term (λ^{-1}) smooths rapid flux changes, functioning as a temporal low-pass filter similar to LSTM gating.

Hopf bifurcation and oscillatory gradients. When the reactor's Jacobian acquires a pair of complex-conjugate eigenvalues with zero real part, a Hopf bifurcation occurs, giving rise to self-sustained neutron-flux oscillations. This mirrors oscillatory gradient dynamics in recurrent neural networks when the dominant eigenvalues of the recurrent weight matrix W_h lie near the unit circle in the complex plane. In both systems, eigenvalues crossing the stability boundary lead to periodic amplification and decay of internal states: the reactor exhibits power fluctuations, while the RNN experiences cyclic gradient magnitudes that hinder convergence. In practice, engineers and machine-learning practitioners alike introduce damping—via negative Doppler feedback or spectral normalization—to push eigenvalues back inside the stability region and ensure asymptotic decay of perturbations.

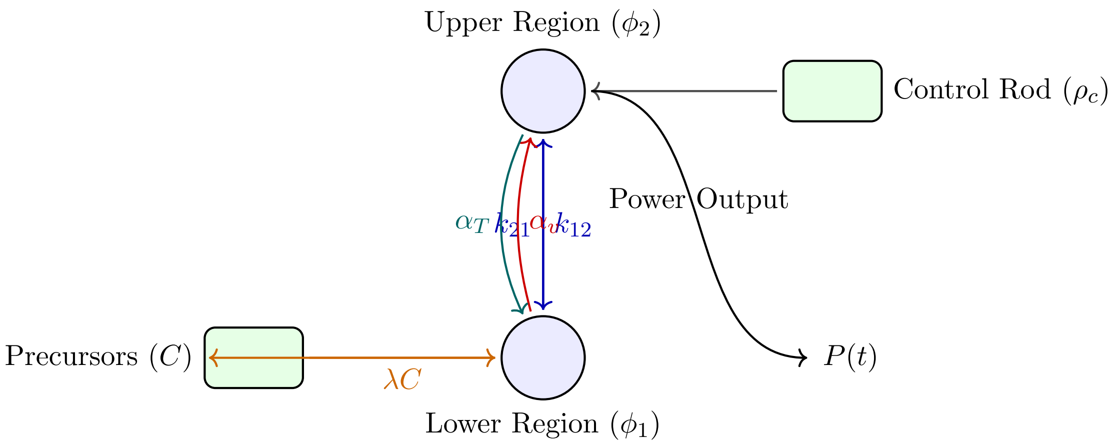

Figure 1: Two-region RBMK reactor represented as a recurrent neural network.

Appendix: Parameter Definitions

Symbol	Meaning	Interpretation in Analogy
ϕ_i	Neutron flux in region i	Hidden state h_t
C_i	Delayed neutron precursor density	Memory variable c_t
ρ_c	Control rod reactivity	External bias term b
α_v	Void coefficient (positive feedback)	Recurrent gain W_h
α_T	Doppler coefficient (negative feedback)	Gradient damping term
β	Delayed neutron fraction	Temporal smoothing weight
λ	Precursor decay constant	Forget gate rate
Λ	Prompt neutron lifetime	Time-step scaling
k_{12}, k_{21}	Coupling coefficients	Recurrent weight sharing
N	Total neutrons (population)	Network normalization