

Week 4 — Deep Equilibrium Networks I

The DEQN Principle & the Brock–Mirman Growth Model

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In PNM you solved the growth model by **value-function iteration** on a grid.

DEQN idea: parameterise the policy function as a neural network and train it to satisfy the equilibrium conditions.

Azinovic, Gaegauf & Scheidegger (2022)

“Deep Equilibrium Nets” — *International Economic Review*

The DEQN Recipe

1. **Define** the economic model (states, controls, equilibrium conditions)
2. **Parameterise** policy functions: $c = \mathcal{N}_\theta(k)$
3. **Construct loss**: squared Euler-equation residuals
4. **Train**: minimise the loss with Adam
5. **Verify**: compare with known solutions or refined grids

No grid, no discretisation of the state space — just sample points.

Brock–Mirman Model

$$\max \sum_{t=0}^{\infty} \beta^t \ln c_t \quad \text{s.t. } k_{t+1} = k_t^\alpha - c_t$$

$$\text{Euler equation: } \frac{1}{c_t} = \beta \frac{\alpha k_{t+1}^{\alpha-1}}{c_{t+1}}$$

Why this model?

It has a **closed-form solution**: $c_t = (1 - \alpha\beta) k_t^\alpha$.

We can verify the neural network against the true answer.

The Euler-equation residual at a sample point k :

$$R(k; \theta) = 1 - \beta \frac{\alpha k'^{\alpha-1} \cdot c(k; \theta)}{c(k'; \theta)}$$

where $k' = k^\alpha - c(k; \theta)$.

$$\text{Loss: } \mathcal{L}(\theta) = \frac{1}{N} \sum_{i=1}^N R(k_i; \theta)^2$$

Train until $\mathcal{L} < 10^{-8}$ — machine-precision accuracy.

- DEQNs replace grid-based VFI with neural-network policy functions
- The loss function encodes economic equilibrium conditions
- Brock–Mirman provides a verifiable first test case
- The method is grid-free and scales to higher dimensions

Next week: adding uncertainty — stochastic models with Gauss–Hermite quadrature.