Sophisticated Modern Control for ITER?

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State of modern control methodologies in plasmas and tokamaks
A.K.Sen, Z.Sun, R.Longman

- In the dim past
  - State feedback and Kalman filter in plasmas
    - A.K.Sen, “state feedback control of multimode plasma instabilities”, IEEE Trans. Plasma Sci., PS-7, 116-119 (1979).
      - And others…
  - Optimal control in plasmas
    - A.K.Sen, “Optimal control of -----”, IEEE Trans. Plasma Sci., PS-9, 41-45 (1981).
      - And others…
  - Followed by a long period of benign neglect

- Recently
  - State feedback and Kalman filters: beginning of new work (APS DPP06)
    - Sporadic citations of original work is perplexing
  - Optimal control (Inclusion of broad-band noise) in RWM
    - Sen, A.K., Nagashima, M., Longman, R.W., (2003), "Optimal control of tokamak resistive wall modes in the presence of noise," Phys. Plasmas, Vol. **10**, No. 11, 4350
    - Fringe benefit: optimal implies some degree of robustness
  - Beginning of recent work (APS DPP06)
    - Again sporadic citations of original work is perplexing

- Adaptive control
  - No work reported so far
  - Necessary for any system which is not totally stationary, especially appropriate for long pulse ITER operation
  - Recently published papers (including noise and optimal control)
    - Sun, Z., Sen, A.K., and Longman, R.W., (2006), "Adaptive optimal stochastic state feedback control of resistive wall modes in tokamaks," Phys. Plasmas, Vol. **13**, No. 1, 012512
    - Sun, Z., Sen, A.K., and Longman, R.W., (2006), "Adaptive optimal output feedback control of resistive wall modes in tokamaks," Phys. Plasmas, Vol. **13**, No. 9, 092508
  - Need serious follow up

Neural network (NN) control Z.Sun, A.K.Sen

- Neural network (NN) control
  - No work reported so far
  - Naturally adaptive
  - System identification and control on the same chip
  - Much faster than sequential algorithms due to massively parallel architecture
  - Suitable for multimode RWM in ITER
  - A preliminary work on this is reported briefly in the next paper, validating the promise

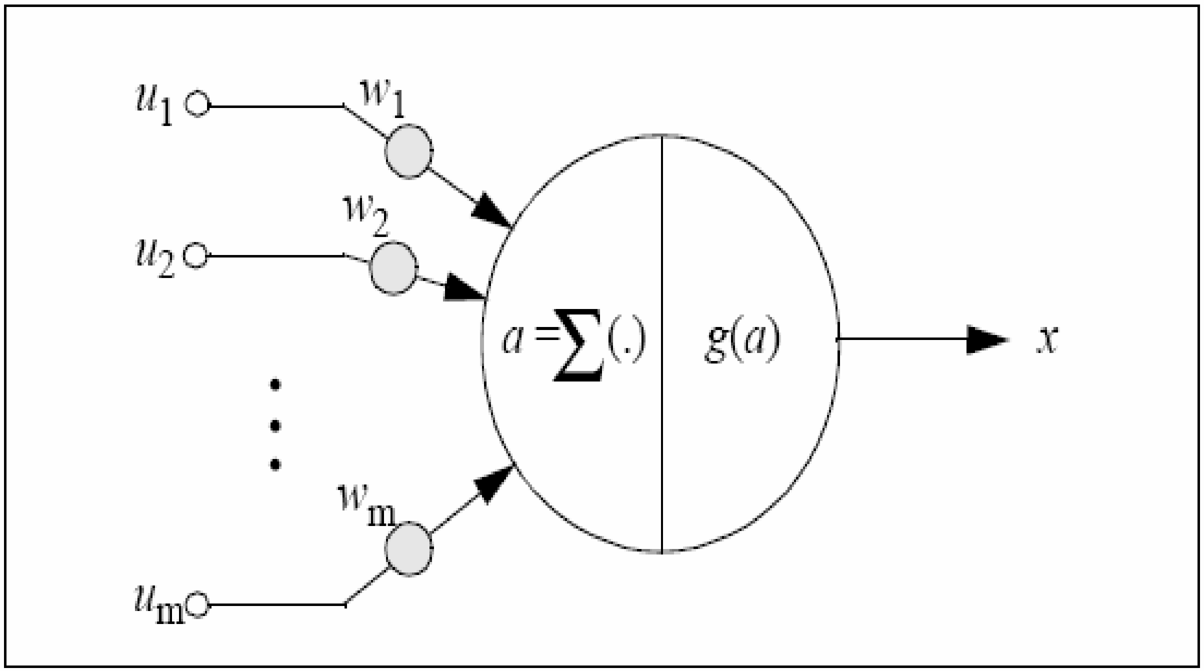


Fig. 1 General functionalities of a neuron

Neural network: general architecture

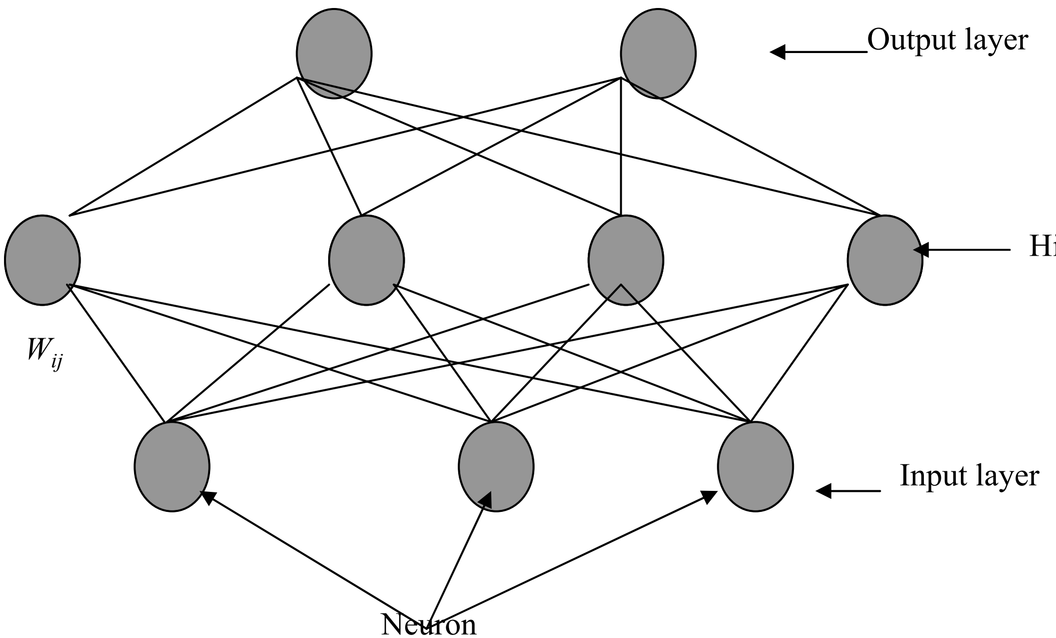
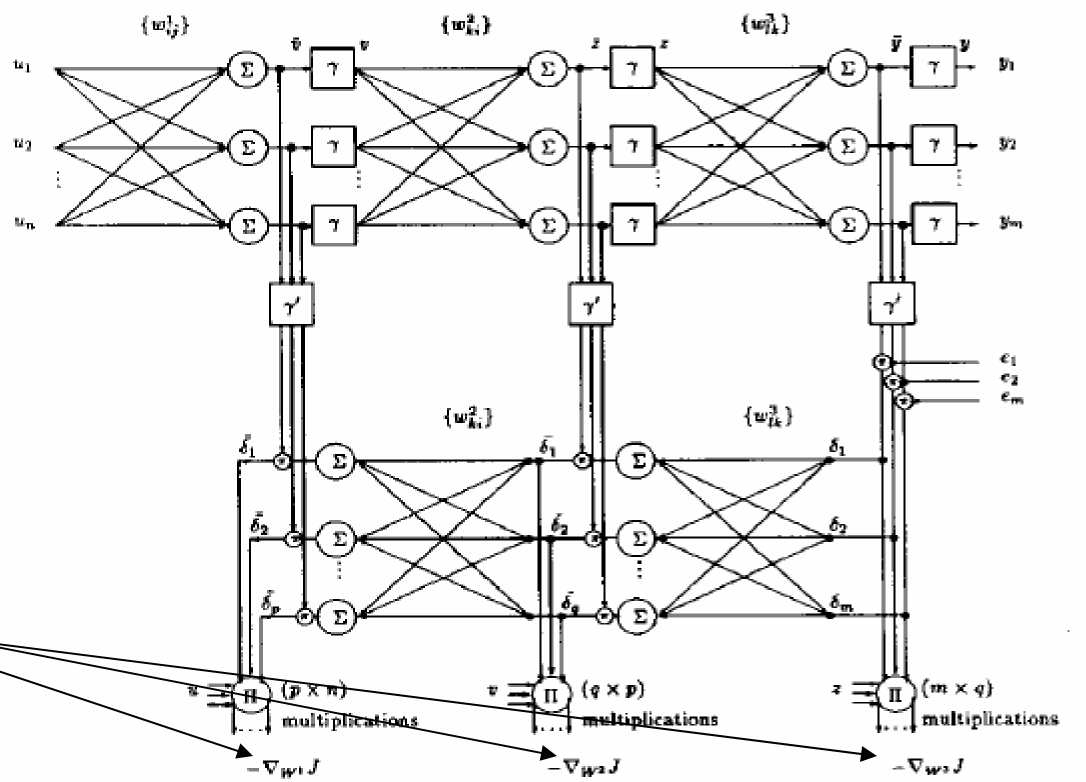


Fig. 2 A diagram of the general architecture of artificial neural networks. Learning/optimality/adaptivity all via adjustment of weights W_{ij}

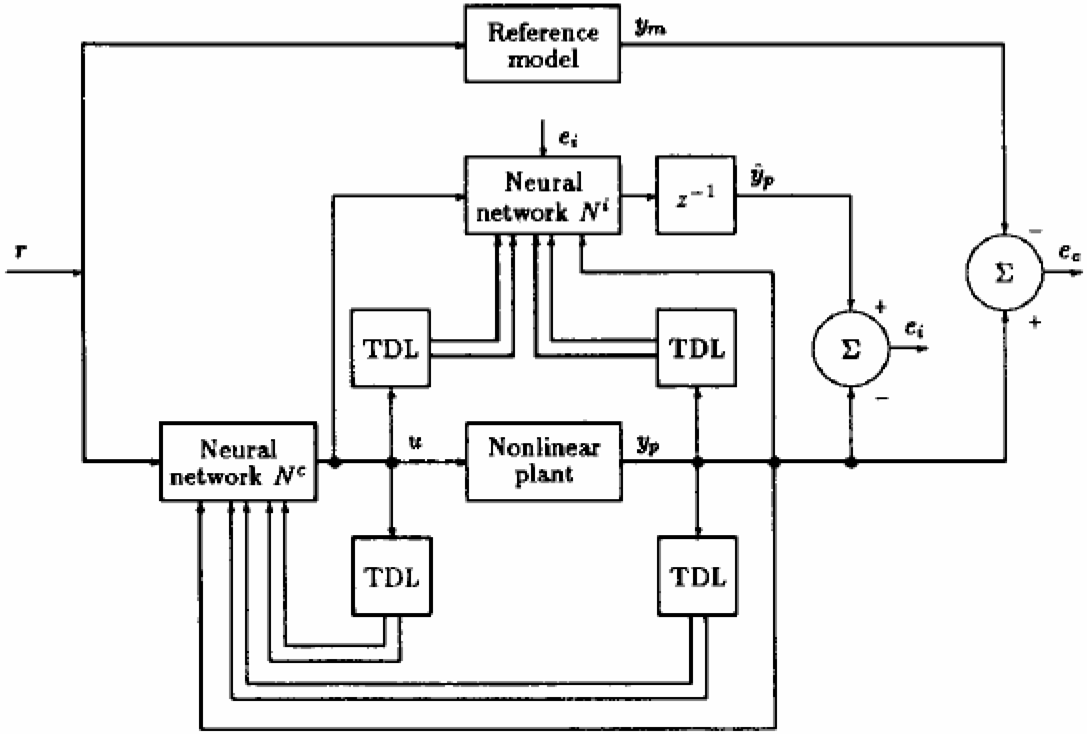
General neural network learning via back propagation



Gradient descent method

Architecture of back propagation. Very useful for nonlinear filtering of colored noise ("ELMs")

Adaptive control via general neural network



Far too general and complicated. Need specialized architecture.

Partial use of neural network in optimal state feedback control

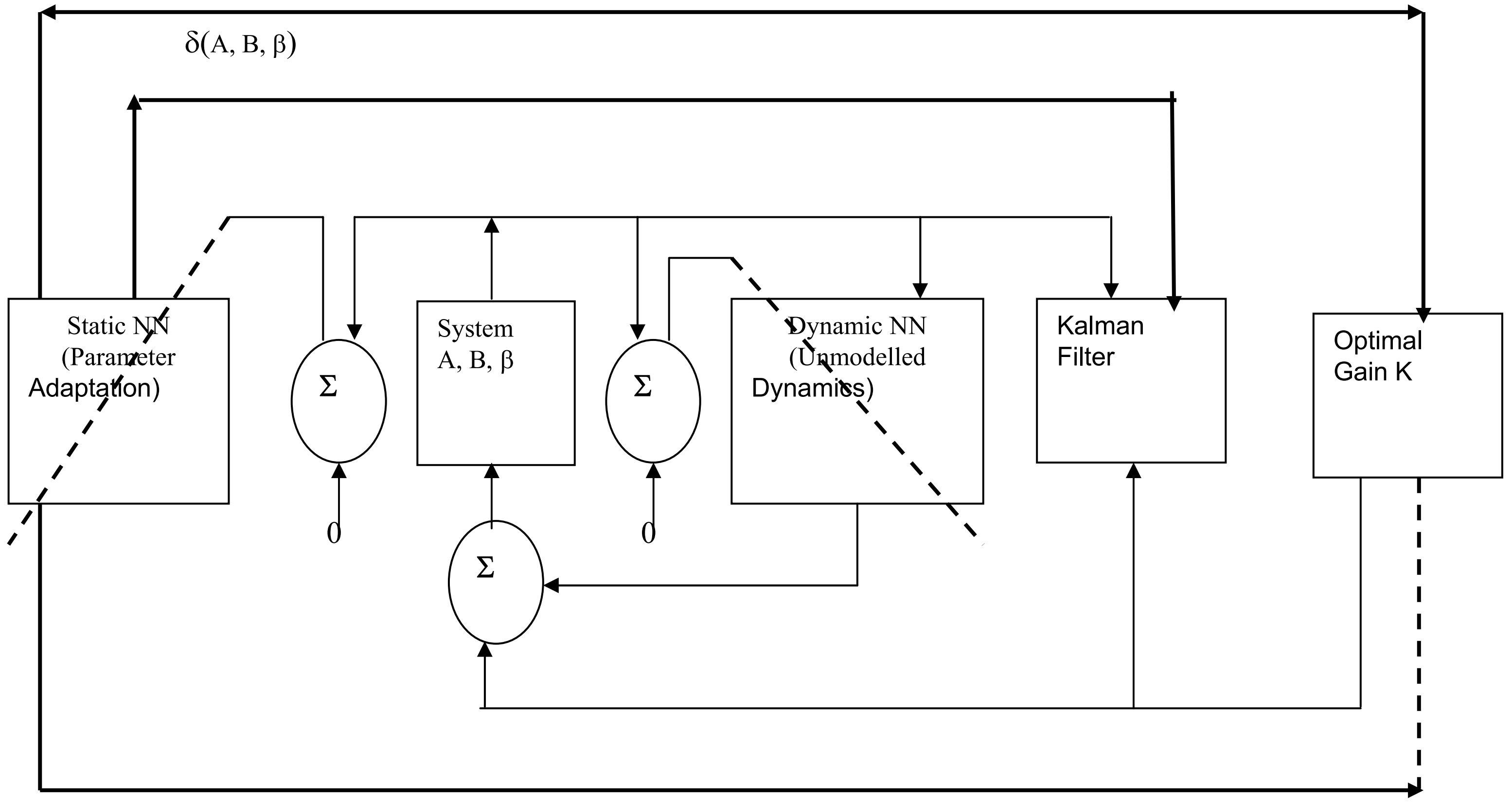


Fig. 3 Adaptive optimal partly NN based controller

Specialized NN architecture for RWM

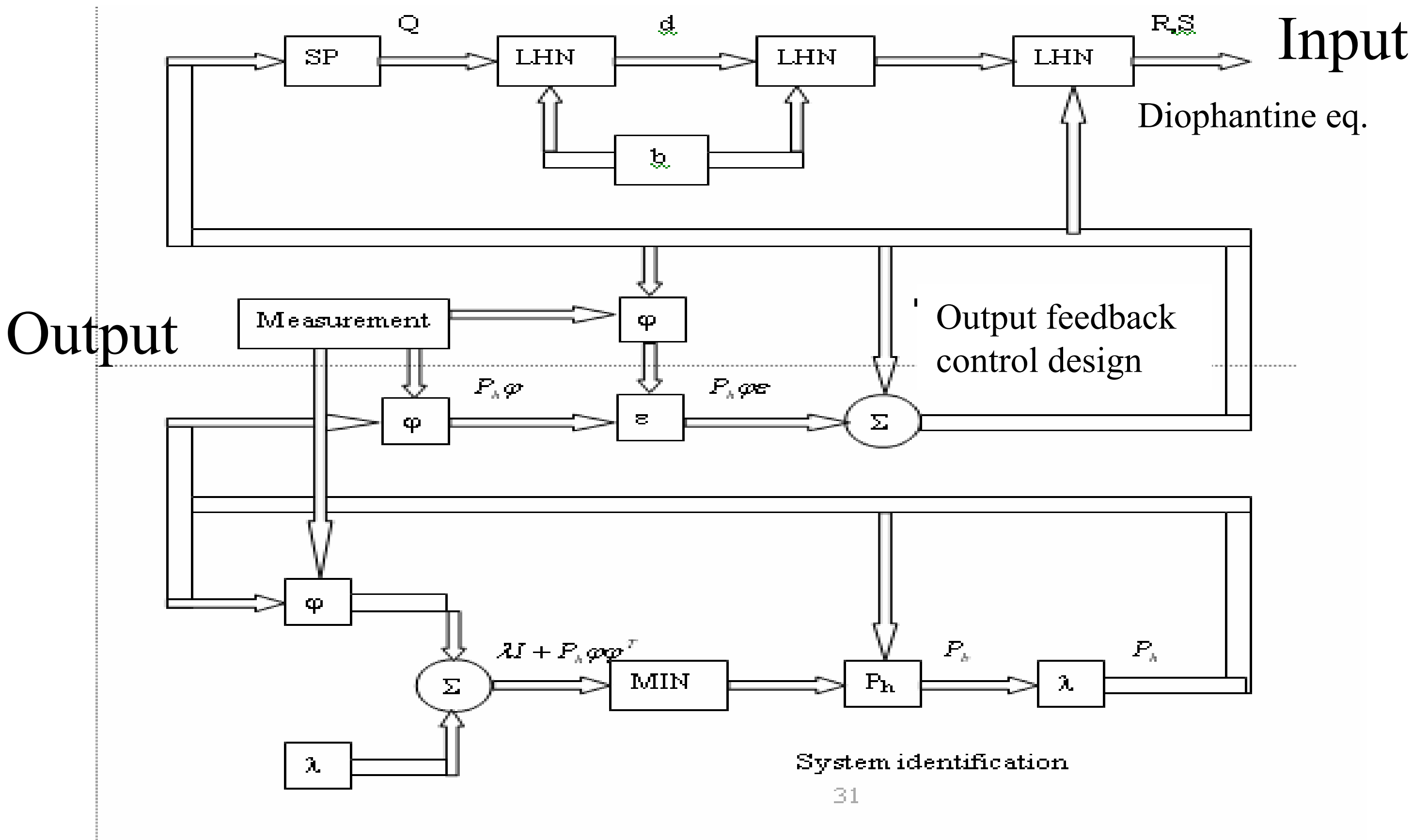
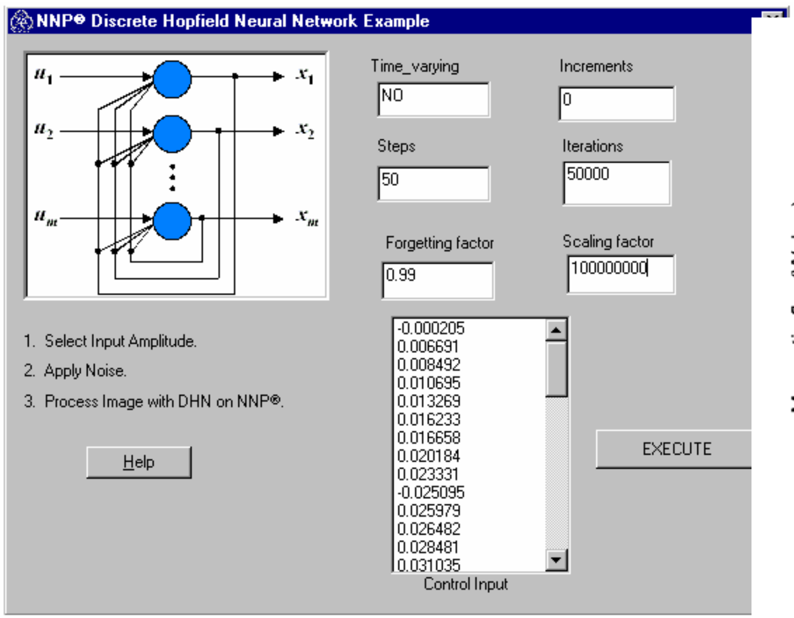
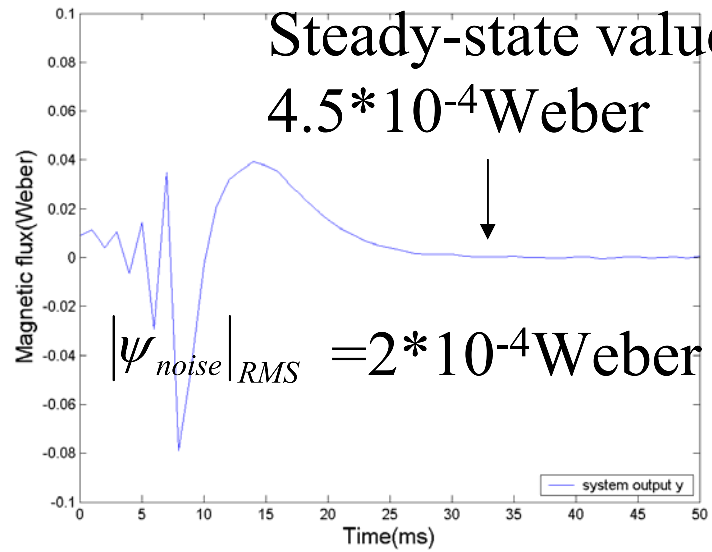


Fig. 4 A neural network architecture, specialized for RWM. LNNs are linear Hopfield networks.

Stabilization of the time-invariant RWM by NN hardware (AAC)

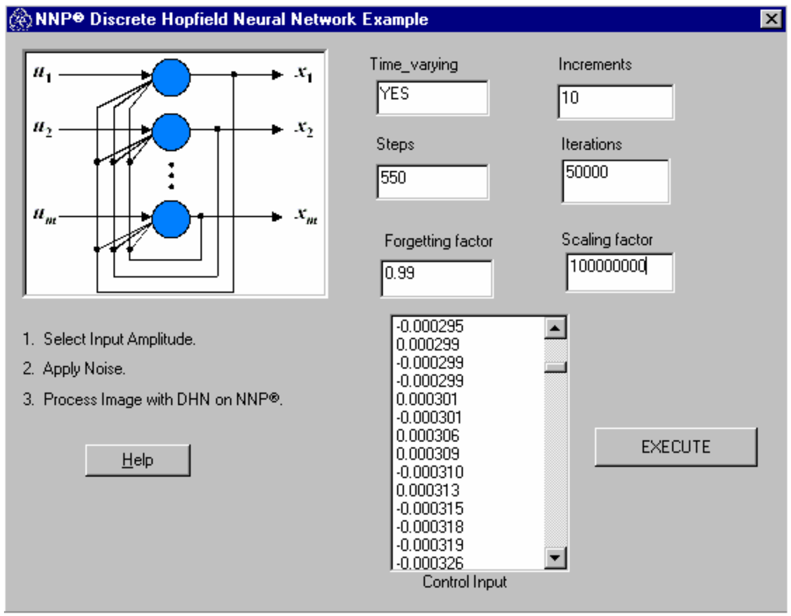


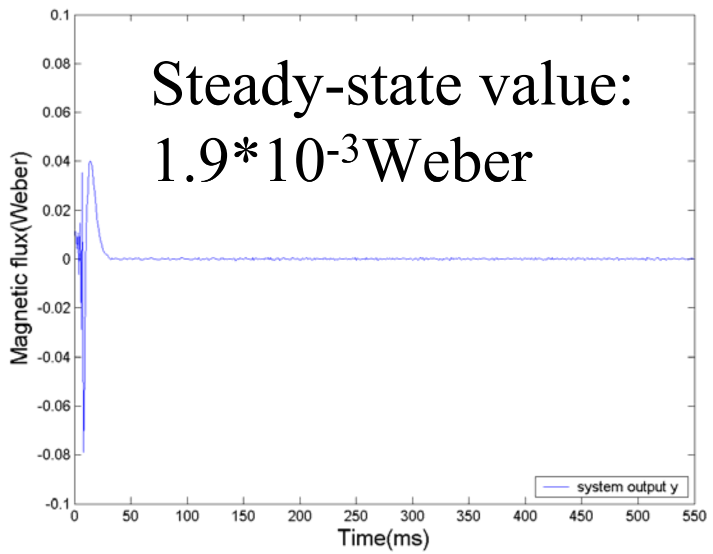


Steady-state value:
$4.5*10^{-4}$Weber

$\left|\psi_{noise}\right|_{RMS} = 2*10^{-4}$Weber

Stabilization of the time-varying RWM by NN hardware (AAC)





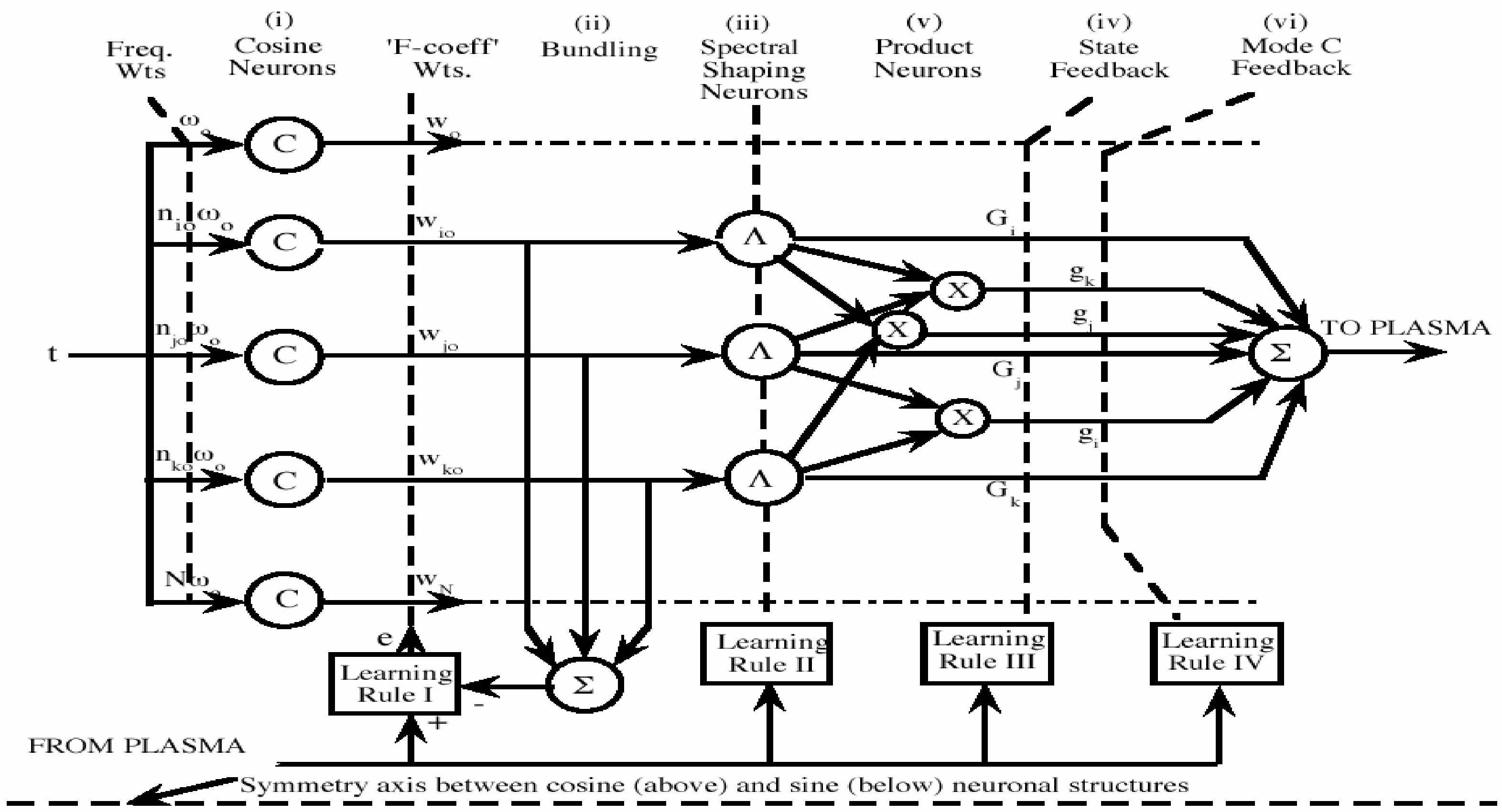
Control of drift wave turbulence A.K.Sen

- In CLM we have experimentally stabilized many types of drift waves (TE, TI, ITG, etc). However,the spectra always contained a few prominent peaks (modes).
- Strong reservations about control of turbulence in tokamaks: nearly continuous spectra with hundreds of modes.
- Now there may be a ray of hope: via neural network control

Neuro-control of drift wave turbulence

- Assumptions and models:
  - Total number of modes (~100)
  - Identify mode packets of strongly coupled triplets (via off-line learning)
  - Choose a subset of large energy triplets (via off-line learning)
  - Feedback stabilize the above via NN of specialized architecture
  - Adjust the above online via adaptive features of NN

Cosine half of FFT state feedback NN with mode shaping and mode coupling



A numerical experiment on dissipative drift wave turbulence

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Univ. of Marseille & CEA, Cadarache, France

Hasegawa, Wakatani model

$$\frac{\partial}{\partial t}(n - \rho^2 \Delta_\perp \Phi) - \rho^2 (\kappa \cdot \nabla)\Phi + \nu \Delta_\perp^2 \Phi = \rho^2 \{n - \rho^2 \Delta_\perp \Phi, \Phi\},$$

$$\frac{\partial}{\partial t}\Delta_\perp \Phi + \omega_s \frac{\partial^2}{\partial z^2}(n - \Phi) = \rho^2 \{\Delta_\perp \Phi, \Phi\},$$

where n and Φ are the density and potential fluctuations, and the Poisson brackets are defined by

$$\{f, g\} = \frac{\partial f}{\partial x}\frac{\partial g}{\partial y} - \frac{\partial g}{\partial x}\frac{\partial f}{\partial y}$$

$$\kappa = z \times \nabla \ln n_0, \ \nabla_\perp = \frac{\partial}{\partial x} + \frac{\partial}{\partial y}.$$

Eigenfunctions

$$\Phi = \Phi_1 \cos z + \Phi_2 \cos 2z$$

with

$$\Phi_{1,2} = \sum_{m,n} A_{m,n}^{(1,2)}(t) \sin(mk_x x) \cos(nk_y y),$$

Retain only 4 modes and add 'modal' feedback

$$\dot{X} = \nu(R-1)X + \tfrac{1}{2} f ZU - XY - jX(t-\tau),$$
$$\dot{Y} = -eY + \tfrac{1}{2}X^2 - 2jY(t-\tau),$$
$$\dot{Z} = -\frac{e}{16} - \frac{1}{4}(1+f)XU - 2jZ(t-\tau),$$
$$\dot{U} = f\nu(R-f)U + \tfrac{1}{2}XZ - fjU(t-\tau),$$

WITHOUT FEEDBACK

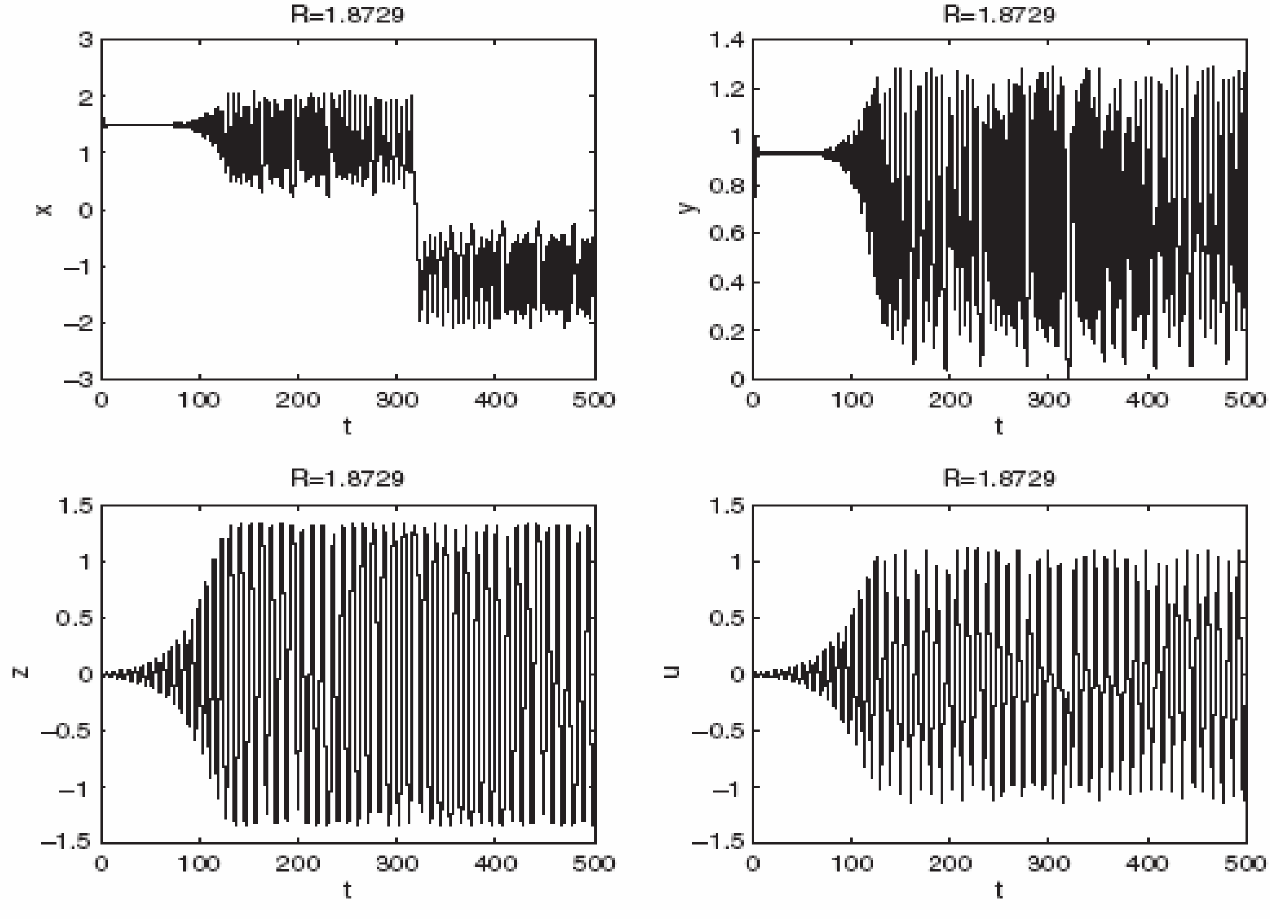


Figure 1. Amplitudes (X, Y, Z, U) in the chaotic case $R = 1.8729$.

WITH FEEDBACK ; $\tau = 0$

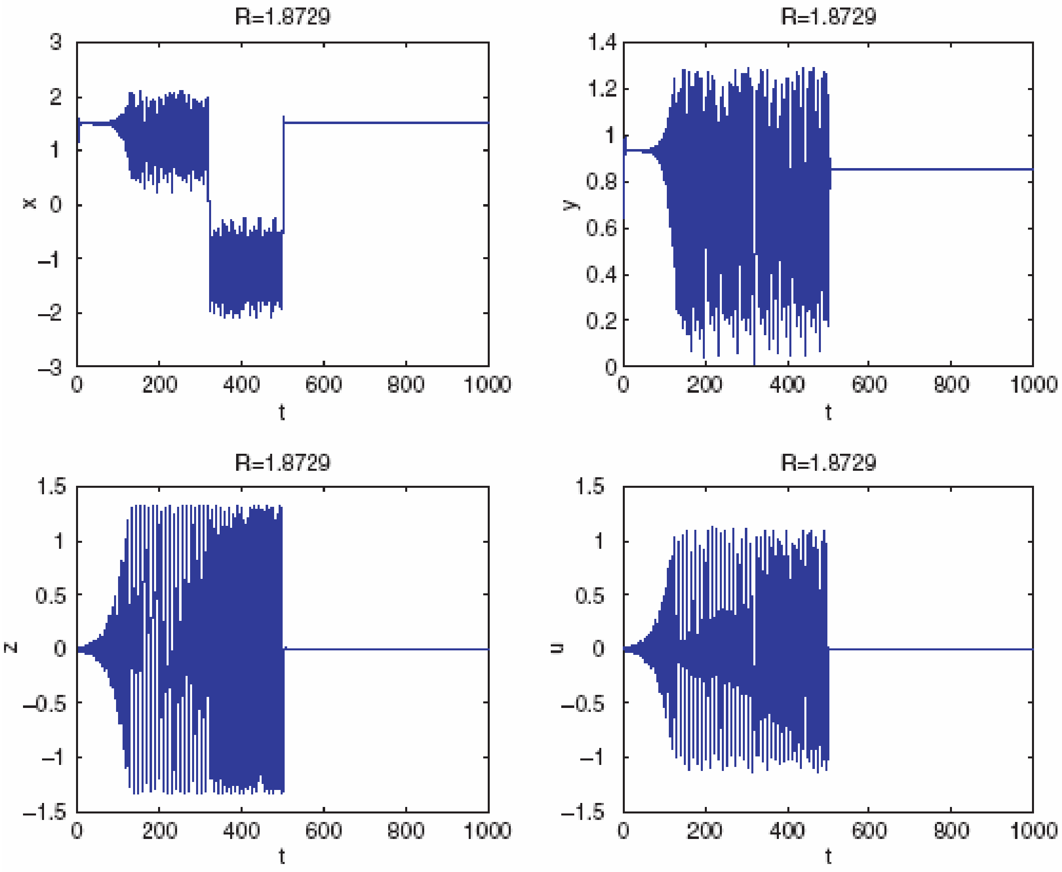


Figure 3. Amplitudes in the chaotic case without time delay, we start feedback control at time $t = 500$, $j = (R - f)v$ (U growth rate set to zero).

WITH FEEDBACK ; $\tau \sim 0.83\ \omega_*^{-1}$

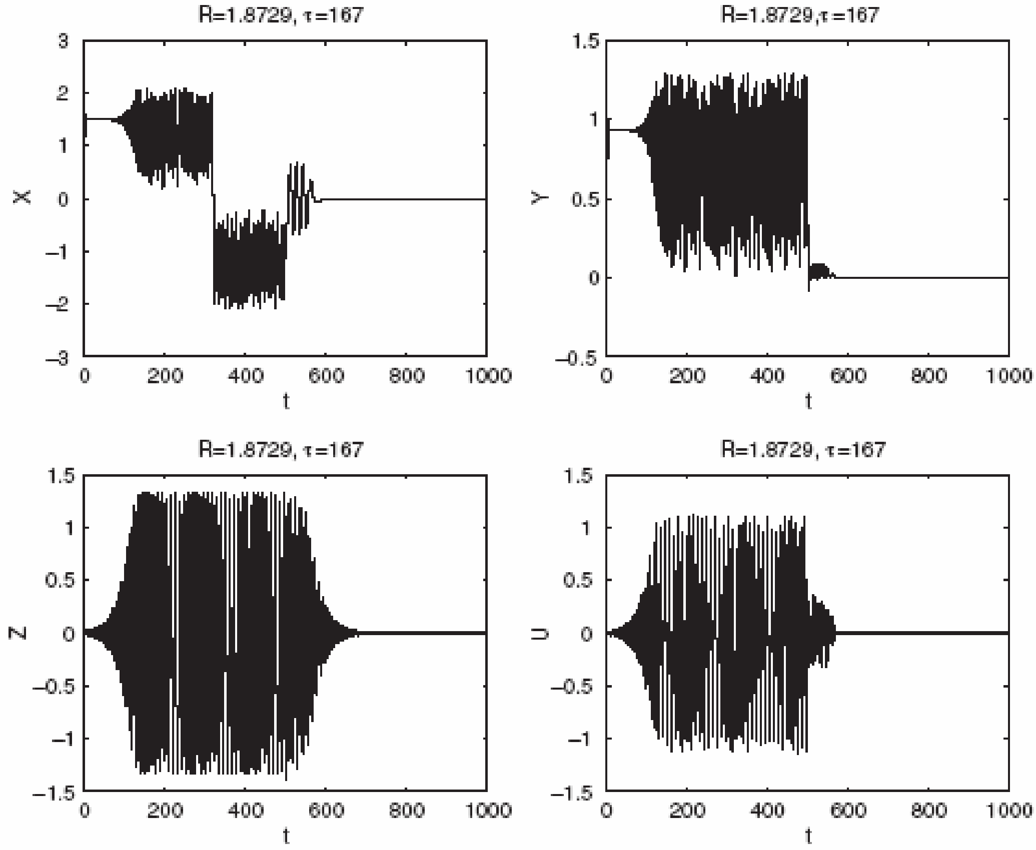
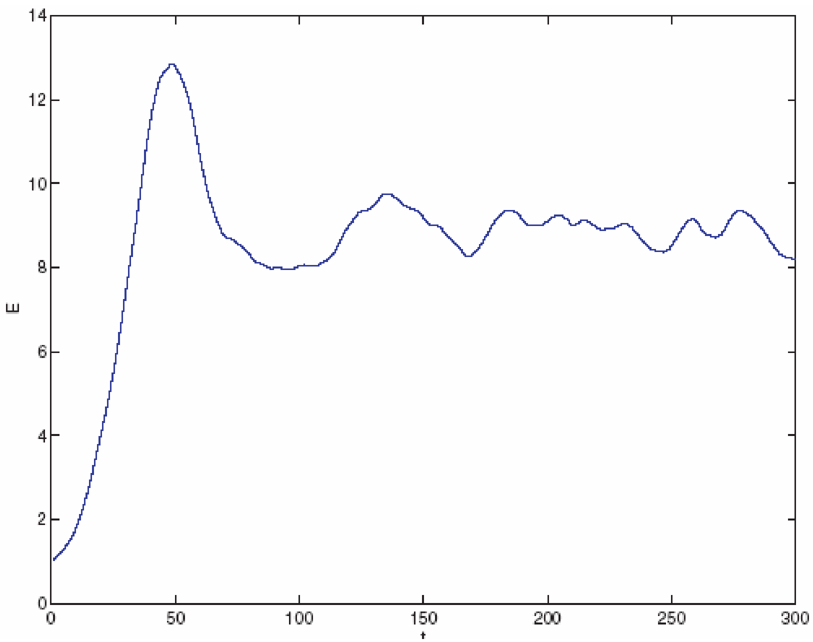
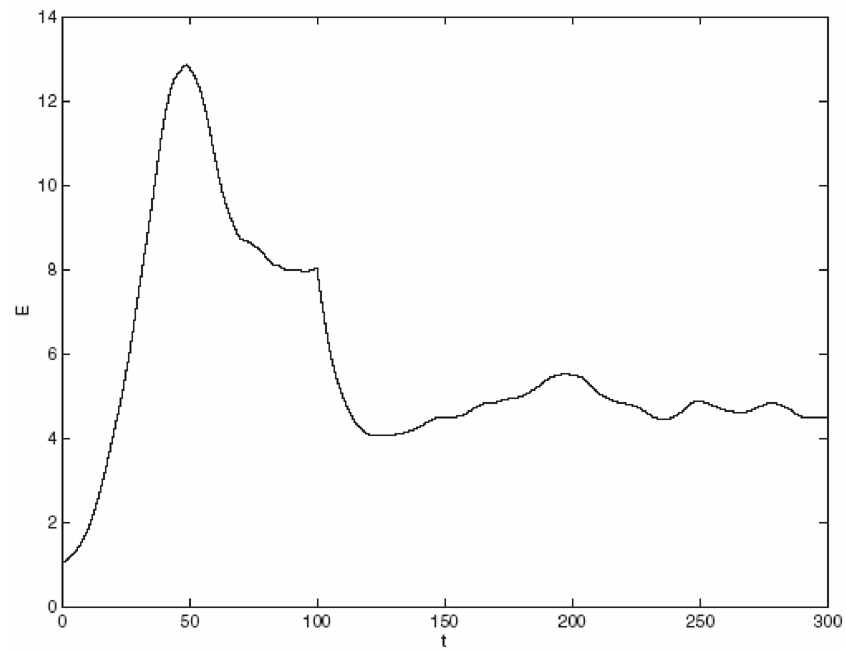


Figure 5. Amplitudes in the chaotic case with a time delay of $\tau = 0.835\omega_*^{-1}$, feedback starts at time $t = 500$ and control is successful.

Time Evolution of Fluctuation Energy Fully Turbulent Case



Without Feedback



Value of α =0.05 without time delay, feedback starts at time t =100

With Feedback

Conclusions

- Now we can and should go beyond PID controllers
- We (the community) may be ready to utilize the advanced control tools for ITER
  - State feedback with Kalman filter
  - Optimal feedback
  - Stochastic formulation of systems with noise
- New challenges
  - Adaptive feedback
  - Neural networks can potentially have substantial impact on all of the above: need a lot of work
  - Neural network for control of plasma turbulence: a remote promise!