FUSION REACTOR BURN CONTROL WITH RADIAL BASIS NEURAL NETWORKS: PRELIMINARY RESULTS

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1. Introduction

In previous work [1] a standard feedforward artificial neural network (ANN) with sigmoidal activation functions was used to demonstrate the capabilities of ANN for the stabilization of burn conditions, at nearly ignited conditions, of a thermonuclear reactor operating in the low temperature region. In this region, the nominal operating point of the fusion reactor is inherently unstable. The purpose of this work is to report the results of the stabilization of this operating point using the same nonlinear fusion reactor model used in Ref. [1], however here we use radial basis neural networks (RBNN) [2] instead of the standard ANN with only sigmoidal units. As before the dynamical evolution of the fusion reactor is represented by the time evolution of the electron density, the relative density of alpha particles and the temperature of the plasma; with an energy confinement time taken from the CDA-ITER scaling law.

The control actions include the concurrent modulation of the D-T refueling rate, the injection of a neutral He-4 beam and an auxiliary heating power. Furthermore, since any feasible control action must be constrained to lie within a set of allowable values, these variables are bounded between maximum and minimum levels. Thus we make use of a feedforward multilayer artificial neural network with radial basis units in the hidden layer and sigmoidal activation units in the output layer. The network was trained in the SGI/CRAY Origin 2000 at UNAM, using a parallel training algorithm developed for this purpose using MPI, a standard portable message passing environment. In Ref. 3 we give details of the parallelization strategy.

2. Physical Model

A zero-dimensional model is adopted in this work to represent a thermonuclear system, in which ions and electrons are assumed to share the same temperature at all times. The plasma is assumed to be solely composed by D-T in equal proportions of alpha particles and electrons. No high-Z impurities are considered. In addition, this model assumes instantaneous thermalization of the alpha particles produced by the fusion reactions, although an estimate of the effect of a finite thermalization time is also performed. Both energy and particle transport are taken into account through an ITER scaling for the energy confinement time τ_E, an alpha particle confinement time τ_α and a D-T fuel confinement time τ_P. Bremsstrahlung is the only radiation loss mechanism included. The evolution of the system is determined by the following set of coupled nonlinear differential equations:

$$\frac{d}{dt}n_{DT} = S - 2\left(\frac{n_{DT}}{2}\right)^2 < \sigma v > -\frac{n_{DT}}{\tau_P}\,, \tag{1}$$

$$\frac{d}{dt}n_\alpha = S_\alpha + \left(\frac{n_{DT}}{2}\right)^2 < \sigma v > -\frac{n_\alpha}{\tau_\alpha}\,, \tag{2}$$

$$\begin{aligned}\frac{d}{dt}\left[\frac{3}{2}(n_e + n_{DT} + n_\alpha)T\right] &= P_{aux} + Q_\alpha\left(\frac{n_{DT}}{2}\right)^2 < \sigma v > + \\ &+ \eta j^2 - A_b Z_{eff}^2 n_e^2 T^{1/2} - \frac{3}{2}(n_e + n_{DT} + n_\alpha)\frac{T}{\tau_E}\,;\end{aligned} \tag{3}$$

which correspond to the D-T and alpha particle densities and the energy density balance equations, respectively. In these equations, S_f represent the refueling rate, S_α the neutral He-4 injection rate, and P_{aux} the auxiliary heating power density; $Q_\alpha = 3.5$ Mev is the energy carried by the fusion alpha particles, $< \sigma v >$ is the D-T reactivity, A_b and η are the coefficients corresponding to the bremsstrahlung radiation losses and the ohmic heating by the plasma current using the neoclassical parallel resistivity, respectively. Here we will assume $\tau_P = 3\tau_E$ and $\tau_\alpha = 7\tau_E$. The energy confinement time is given by the following scaling law,

$$\tau_E = 0.082\, I_p^{1.02}\, R^{1.6}\, B_0^{0.15}\, A_i^{0.5}\, \kappa_x^{-0.19}\, P_{net}^{-0.47}\,; \tag{4}$$

where $P_{net} = V_{core}(P_{aux}+P_\alpha+P_{oh}-P_{br})$. Using the quasineutrality condition $n_e = n_{DT}+2n_\alpha$, the above set of equations can be transformed into a set of equations for the electron density n_e, the relative fraction of alpha particles $f = n_\alpha/n_e$ and the plasma temperature T. The ignited steady state condition, $i.e.$ where $P_{aux} = 0$ and $S_\alpha = 0$, is obtained for $S_o = 4.16 \times 10^{18}$ m^{-3}sec^{-1} with $n_0 = 9.8 \times 10^{19}$ m^{-3}, $T_0 = 8.28$ Kev and $f_0 = 0.0624$, values that will be assumed to constitute the desired operating point for the ignited tokamak reactor of this work.

It is desired to stabilize the dynamical system through the use of a RBNN to provide a control law of the form $\vec{u} = \vec{u}(\vec{z})$, such that perturbations in the state variables are suppressed by the neural network, returning to the nominal operating point. The joint RBNN-dynamical system configuration is illustrated in Fig. 1, where the output of the neural network $\vec{u}$ is associated with the control variables $S_f,\ S_\alpha$ and P_{aux} through the following transformation equations: $S_f = S_0 k_1 u_1$, $S_\alpha = f_0 n_0 k_2 (2u_2 - 1)^2$ and $S_{aux} = 1.5 n_0 T_0 k_3 (2u_3 - 1)^2$; with the following arbitrary values $k_1 = 4, k_2 = 0.1$ and $k_3 = 0.1$.

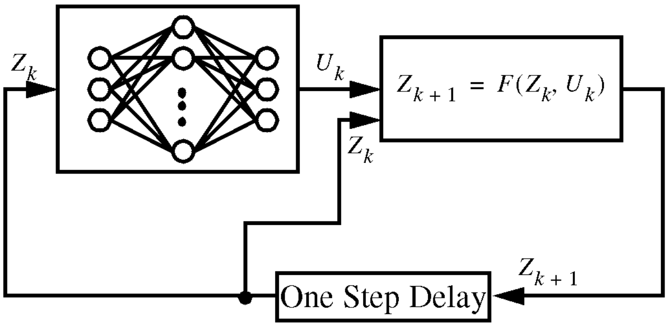

Figure 1. RBNN - dynamical system configurationa.

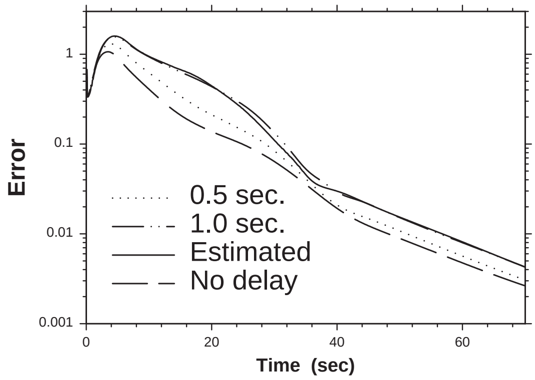

Figure 1. Time behavior of the total error $\mathcal{E}$, associated to the 64 trajectories as discussed in the text, for different thermalization time delays.

3. Training Results and Alpha Particles Thermalization Time Effect

After some preliminary training sessions, a successful RBNN was obtained and the results were similar to those obtained previously[1] using sigmoidal activation functions, but the convergence was obtained in shorter times. A set of simulation results were performed to test the stability of the entire system with respect to finite thermalization times assuming constant time delays of 0.5 s and 1.0 s in the energy deposited by the alpha particles, as well as a state dependent estimated thermalization time given by $\tau_{th} = 2.1 \times 10^{18} T_0^{3/2} n_0^{-1} z_3^{3/2} z_1^{-1}$ [1] . In Fig. 2 we show the total cumulative error $\mathcal{E}$ as function of time of 64 trajectories for each one of the cases. Each trajectory was generated by assigning one of the following four initial values: 0.92, 0.9733, 1.0266, and 1.08 to each of the different normalized state variables.

4. Conclusions

In this work we present some preliminary results obtained with a parallel NN training code, concerning the use of radial basis neural networks for the stabilization of a thermonuclear reactor at nearly ignited burn conditions. The results show that a satisfactory learning has been obtained for perturbations within the training region i.e. perturbations within $\pm$ 10% of their nominal operating values; simulation results further show that the RBNN-dynamical system is robust with respect to the thermalization time of the alpha particles for perturbations within $\pm$ 8% off their nominal operating value.

Acknowledgments

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