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Stabilization of Fusion Reactor Burn Conditions with Radial Basis Neural Networks

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1 Introduction

In previous works we reported the development of two artificial neural networks for the stabilization at ignited burn conditions of a thermonuclear reactor using the CDA ITER scaling law and design parameters: a standard feedforward NN with sigmoidal activation functions and a radial basis neural network (RBNN) with Gaussian functions in the hidden layer and sigmoids in the output layer, as depicted in Fig. 1.[1] Here we report some preliminary results concerning the stabilization at sub-ignited conditions of a thermonuclear reactor by means of a RBNN, using the parameters from the EDA ITER design group. In this work, however, instead of using a scaling law for the energy confinement time,[2] we consider the energy confinement time as an input parameter to the RBNN and trained the network to provide feedback stabilization for a range of confinement times. The control actions include the modulation of the D-T refueling rate, the injection of a neutral He-4 beam as well as an auxiliary heating power. The network was trained using a parallel training code developed using MPI a portable message passing enviroment, and its structure is similar to the one reported in Ref. 3 but modified to work with radial basis neural networks. The platform used was the SGI/CRAY Origin 2000 at UNAM.

2 Tokamak Model

The tokamak fusion reactor model used here is a zero-dimensional plasma system composed by D-T in equal proportions, helium ions, a small fraction of high-Z impurities and electrons, where the quasineutrality condition $n_e = n_{DT} + 2n_\alpha + Z_i n_i$ is satisfied. All particles in the system are taken to be at the same temperature, and the alpha particles produced by the fusion reactions are assumed to be instantaneously thermalized. Bremsstrahlung is the only radiation loss mechanism considered and transport losses are taken into account through the energy confinement time τ_E, as well as by the D-T and the alpha particle confinement times, τ_p and τ_α respectively. The model also assumes that the density n_i and effective charge Z_i of the impurities remain constant at all times. With these assumptions the following set of coupled nonlinear differential equations for the electron density n_e, the relative fraction of alpha particles $f_\alpha = n_\alpha/n_e$, and the plasma temperature T, are obtained:

$$\frac{dn_e}{dt} = S_f - \left(\frac{2f_\alpha}{\tau_\alpha} + \frac{1-2f_\alpha}{\tau_p}\right)n_e + \frac{Z_i n_i}{\tau_p} + 2S_\alpha \ , \tag{1}$$

$$\frac{df_\alpha}{dt} = \frac{1}{4}n_e(1-2f_\alpha - \frac{Z_i n_i}{n_e})^2 < \sigma v > - \frac{f_\alpha}{n_e}\frac{Z_i n_i}{\tau_p} - \frac{f_\alpha}{n_e}S_f + f_\alpha(1-2f_\alpha)\left(\frac{1}{\tau_P} - \frac{1}{\tau_\alpha}\right) + S_\alpha \frac{1}{n_e}(1-2f_\alpha) \ , \tag{2}$$

$$\begin{aligned}\frac{dT}{dt} = {} & \left(\frac{1}{6}Q_\alpha + \frac{1}{4}T\right)n_e < \sigma v > \frac{(1-2f_\alpha - Z_i n_i/n_e)^2}{2-f_\alpha-(Z_i-1)n_i/n_e} + 2\frac{(1-2f_\alpha - Z_i n_i/n_e)}{2-f_\alpha-(Z_i-1)n_i/n_e}\frac{T}{\tau_P} - \\ & \frac{2}{3}A_b\frac{(1+2f_\alpha+Z_i(Z_i-1)n_i/n_e)}{2-f_\alpha-(Z_i-1)n_i/n_e}n_e T^{1/2} - \frac{T}{\tau_E} + \frac{3f_\alpha}{2-f_\alpha-(Z_i-1)n_i/n_e}\frac{T}{\tau_\alpha} + \\ & \frac{2}{3}A_h\frac{(1+2f_\alpha+Z_i(Z_i-1)n_i/n_e)^{0.5}}{n_e(2-f_\alpha-(Z_i-1)n_i/n_e)T^{3/2}} \times \\ & \frac{1+1.198(1+2f_\alpha+Z_i(Z_i-1)n_i/n_e)^{0.5}+0.222(1+2f_\alpha+Z_i(Z_i-1)n_i/n_e)}{1+2.966(1+2f_\alpha+Z_i(Z_i-1)n_i/n_e)^{0.5}+0.75(1+2f_\alpha+Z_i(Z_i-1)n_i/n_e)} - \\ & \frac{T}{n_e(2-f_\alpha-(Z_i-1)n_i/n_e)}(2S_f+3S_\alpha) + \frac{2}{3}\frac{P_{aux}}{n_e(2-f_\alpha-(Z_i-1)n_i/n_e)} \ ;\end{aligned} \tag{3}$$

where $Q_\alpha = 3.5$ Mev is the energy carried by the fusion alpha particles, $< \sigma v >$ is the D-T reactivity, A_b and A_h are respectively, the coefficients of the bremsstrahlung radiation losses and the ohmic heating by the plasma current assuming neoclassical parallel resistivity. In this work we will assume $\tau_P = 3\tau_E$ and $\tau_\alpha = 5.5\tau_E$. The control actions are represented by, S_f the refueling rate, S_α the neutral He-4 injection rate, and P_{aux} the injection rate of the auxiliary heating power density.

The nominal operating state, was determined from the ignited steady state condition, *i.e.* $P_{aux} = 0$ and $S_\alpha = 0$, corresponding to the EDA ITER design parameters and its associated energy confinement scaling law.[2,4] This leads us to $n_0 = 1.0 \times 10^{20}$ m^{-3}, $T_0 =$ 12 Kev and $f_0 = 0.09$, an energy confinement time $\tau_e = 7.63$ sec and a DT refueling rate of $S_o = 3.58 \times 10^{18}$ m^{-3}sec^{-1}; where it was assumed that 96% of the alpha particles energy produced by the fusion reactions is deposited within the system; the high-Z impurity density is $n_i = 7.0 \times 10^{17}$ m^{-3} with an effective charge $Z_i = 14.7$. The above values of the plasma temperature, the electron density and the fraction of helium ash constitute the operating point for the sub-ignited tokamak reactor we are concerned with in this work.

The RBNN was trained to stabilize the system, suppressing perturbations within 10% below their nominal operating values for a range of energy confinement times τ_e, which was chosen here to lie between 6.25 sec and 7.25 sec, yielding a control law $\vec{u} = \vec{u}(\vec{z}, \tau_e)$.

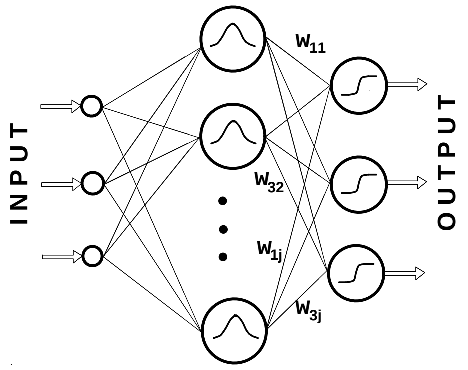

Figure 1: Radial basis neural network with sigmoidal output units.

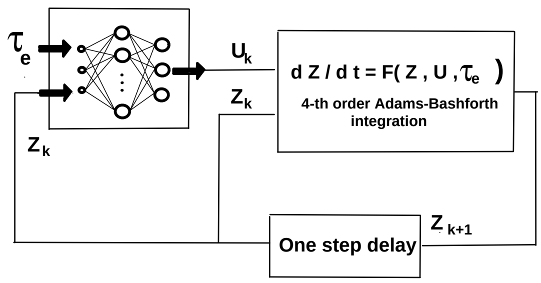

Figure 2: RBNN - dynamical system configuration.

3 Results

The joint RBNN-dynamical system configuration is illustrated in Fig. 2, where the output of the neural network $\vec{u}$ is associated with the control variables and are constrained to take values within the following range $0 \leq S_f \leq 4 \times S_0$, $0 \leq S_\alpha \leq 0.1 \times f_0 n_0$ and $0 \leq P_{aux} \leq 0.2 \times 1.5 n_0 T_0$. The resulting RBNN required 151 training iterations in order to succesfully suppress perturbations up to 10% below their nominal operating values. We present here two illustrative examples of the results obtained after the neural network training. The initial state in both cases is $n = 0.90 \times n_0$, $f_\alpha = 0.95 \times f_0$, and $T = 0.95 \times T_0$. In the first case it is assumed an energy confinement time $\tau_e = 6.25$ sec, while in the second $\tau_e = 7.25$ sec. Figures 3 and 4 show the time behavior of the state and control variables for the first 10 sec into the transient, corresponding to these two cases; in these figures the state variables are shown normalized to their nominal operating values, while the control variables are normalized to $4 \times S_0$ m^{-3} sec^{-1}, $0.1 \times n_o\, f_o$ m^{-3} sec^{-1}, and $0.2 \times 1.5 \times n_0\, T_0$ Kev m^{-3} sec^{-1} for the DT refueling rate, the neutral helium and the auxiliary energy injection rates, respectively. It is observed that the neural network controller is able to suppress perturbations in the state variables returning to their nominal values within the first 12 sec into the transient, as shown in these figures.

4 Conclusions

Preliminary results are presented, concerning the use of a RBNN for the stabilization of a thermonuclear reactor at subignited burn conditions for a range of energy confinement times between 6.25 sec and 7.25 sec. Simulation results were used to illustrate the behavior of the RBNN-dynamical system for two different energy confinement times within the training region. Further research is being done to include also perturbations above the nominal operating point as well as to increase the energy confinement time range for which the NN performs satisfactorily.

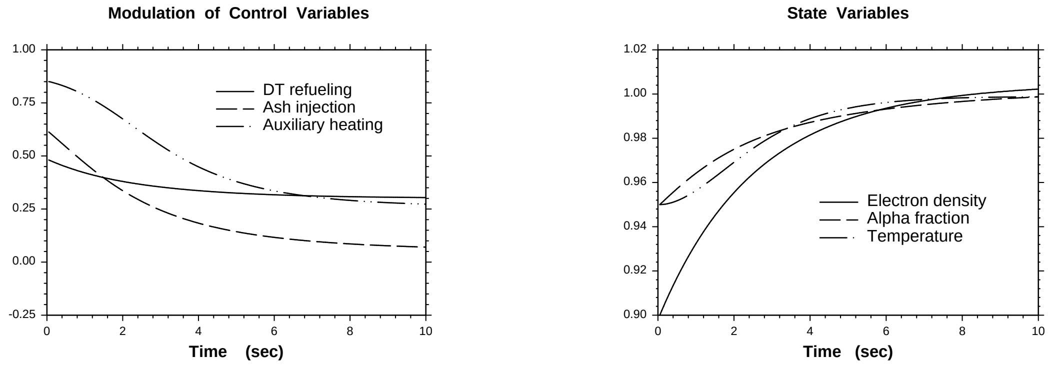

Figure 3: Behavior of the normalized control variables (left) and state variables (right) as function of time, for an energy confinement time $\tau_e = 6.25$ sec.

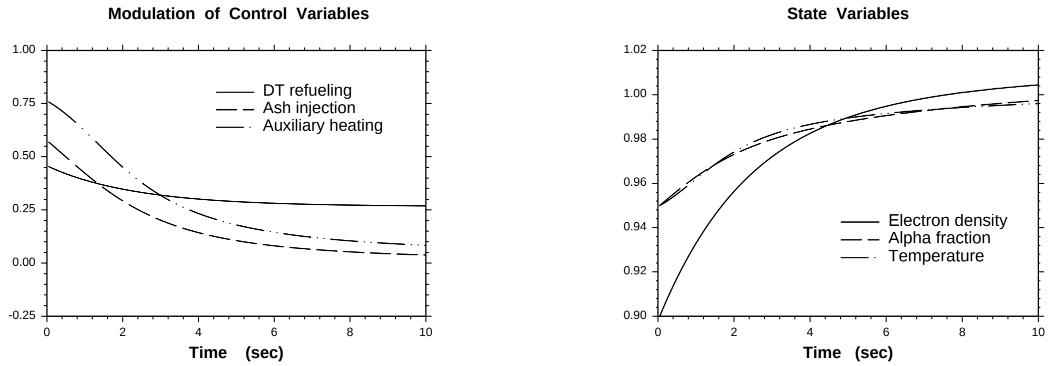

Figure 4: Behavior of the normalized control variables (left) and state variables (right) as function of time, for an energy confinement time $\tau_e = 7.25$ sec.

Acknowledgments

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