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Robust Stabilization of Burn Conditions in Subignited Fusion Reactors using Artificial Neural Networks

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Abstract

In this work it is shown that robust burn control in long pulse operations of thermonuclear reactors can be succesfully achieved with artificial neural networks. The results reported here correspond to a volume averaged zero-dimensional nonlinear model of a subignited fusion device using the design parameters of the tokamak EDA-ITER group. A Radial Basis Neural Network (RBNN) was trained to provide feedback stabilization at a fixed operating point independently of any particular scaling law that the reactor confinement time may follow. A numerically simulated transient is used to illustrate the stabilization capabilities of the resulting RBNN when the reactor follows an ELMy scaling law corrupted with Gaussian noise.

Keywords:

thermonuclear reactors, burn condition stabilization, artificial neural networks, nonlinear control

1. Introduction

It is now widely recognized by the fusion community that particle and energy transport in magnetically confined devices are determined mainly by turbulent processes. However, theoretical and numerical predictions of transport properties are a formidable task involving highly nonlinear phenomena and thus in spite of major advances achieved in this field, significant discrepancies with experimental results still exist. Current design studies are then generally performed using transport losses modelled through a global energy confinement time, extrapolated using a comprehensive data base gathered from previous and current tokamak experiments. Hence, the resulting ITER scaling laws for the L- and H-mode cases whether under ELMy or ELM-free operating conditions, suffer from significant uncertainties [1]. Thus, it is important for the long pulse operation of the next generation machines to have reliable means for plasma burn stabilization which are independent of any particular scaling law, as well as robust with respect to noise or to stochastic fluctuations inherent to measurements and turbulent processes underlying transport phenomena.

The purpose of this work is to show that robust burn control in long pulse operations of thermonuclear reactors can be succesfully achieved with artificial neural networks. Although there are well established control design techniques for linear dynamical systems, being the most populars the PID controllers, their applications to nonlinear dynamical systems require a linearization procedure which may restrain their applicability range. On the other hand with the use of nonlinear controllers such as artificial neural networks, it is expected to extend the range of applicability, while at the same time taking into account design restrictions

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such as the maximum and the minimum levels that actual control actions can take [2].

In a previous work [3] we reported the development of a standard feedforward artificial neural network with sigmoidal activation functions, for the stabilization at ignited burn conditions of a thermonuclear reactor with the CDA ITER scaling law and design parameters. In this work we present results concerning the stabilization at subignited burn conditions of a thermonuclear reactor, with the parameters of the tokamak EDA ITER [4], which is independent of any particular scaling law. Hence, we can not determine the thermal stability at the operating point since this depends on the specific scaling law of the device. To ensure the stability of the reactor regardless of the scaling of the energy confinement time, we train a Radial Basis Neural Network (RBNN) [5] with Gaussian nodes in the hidden layer and sigmoidal units in the output, to provide feedback stablization at a fixed operating point by considering the energy confinement time as part of the input parameters to the network.

In order to have the same operating point for the family of subignited devices with different scaling laws considered here, it is required that the control actions include the injection of a neutral He-4 beam in addition to the D-T refueling rate and the auxiliary heating power. This is due to the fact that these variables need to be adjusted properly for steady state at the operating point for different values of the energy confinement time.

2. Tokamak Model

The tokamak reactor model used here is a zero-dimensional volume averaged plasma system composed by D-T in equal proportions with density n_{DT}, helium ions n_α, low density high-Z impurities n_I, and electrons n_e; 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. In addition, similarly to other studies [6], the model assumes that the density n_I and the charge Z_I of the high-Z impurities remain constant at all times.

The thermonuclear reactor model considered here, is described by the following equations,

$$\frac{d}{dt} n_{DT} = S_f - 2\left(\frac{n_{DT}}{2}\right)^2 <\sigma v> - \frac{n_{DT}}{\tau_p}, \qquad (1)$$

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

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

where $Q_\alpha = 3.5$ MeV is the energy carried by the fusion alpha particles, $<\sigma v>$ is the D-T reactivity [7], A_b is the coefficient of the bremsstrahlung radiation losses and ηj^2 is the ohmic heating density by the plasma toroidal current [8]. In particular 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.

Using the quasineutrality condition, these equations can be transformed into a set of coupled nonlinear differential equations for the electron density n_e, the relative fraction of helium ash $f_\alpha = n_\alpha/n_e$, and the plasma temperature T. The nominal operating point, 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 ELM-free energy confinement scaling law [9], i.e.

$$\tau_E = 0.031 I^{0.95} R^{1.92} B^{0.25} M^{0.42} \varepsilon^{0.08} \kappa^{0.63} n_e^{0.35} P_{net}^{-0.67}; \qquad (4)$$

where n_e is the electron density and P_{net} represent the total net plasma heating including auxiliary heating.

The volume averaged values of the operating point are $n_0 = 1.0 \times 10^{20}$ m^{-3} for the electron density, $T_0 = 12$ keV for the plasma temperature and $f_{\alpha 0} = 0.09$ for the ash fraction, with a DT refueling rate of $S_{f0} = 3.58 \times 10^{18}$ m^{-3}sec^{-1}. Eq. 4 yields an energy confinement time $\tau_E = 7.63$ sec for an ignited device. In the above calculations it was assumed that 96% of the alpha particles energy produced by the fusion reactions is deposited within the system; and the high-Z impurity density is $n_I = 7.0 \times 10^{17}$ m^{-3} with a 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 reactors we are concerned with in this work.

Although the auxiliary heating power and the neutral He-4 beam injection are zero for an ignited device i.e. with $\tau_E = 7.63$ sec as pointed out above, they must be different from zero if the same operating point $\{n_0, f_{\alpha 0}, T_0\}$ is desired for subignited devices, i.e with smaller τ_E, regardless of the scaling law.

3. Training and Simulation Results

The network was trained using dynamic backpropagation [10] with a parallel training code developed using MPI a portable message passing enviroment [11], and modified to work with radial basis neural networks. The multiprocessor platform used was the SGI/CRAY Origin 2000 at UNAM. The RBNN was trained to stabilize the system, suppressing perturbations around the nominal operating point for a range of energy confinement times τ_E, that was chosen here to lie between 5.0 sec and 6.5 sec; this time range corresponds to subignited devices since they are below the value of 7.63 sec required for ignition. The closed loop RBNN-dynamical system configuration is illustrated in Fig. 1, 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 $0 \le S_f \le 4 \times S_{f0}$ m^{-3}sec^{-1}, $0 \le S_\alpha \le 0.1 \times f_{\alpha 0} n_0$ m^{-3}sec^{-1} and $0 \le P_{aux} \le 0.2 \times 1.5\, n_0 T_0$ keV m^{-3}sec^{-1}, or in terms of the total auxiliary heating power $0 \le P_{total} \le 115$ MW. In addition to the energy confinement time τ_E, the input to the network is composed by the current values of the electron density, the fraction of helium ash and the plasma temperature. The training of the RBNN was performed with numerically simulated transients using a fourth order Adams-Bashforth integrating scheme, with initial perturbations in the state variables within 10% below and 8% above their nominal values and different values of the confinement time for each transient. As a training strategy the values of τ_E were kept constant for the entire duration of the individual transients.

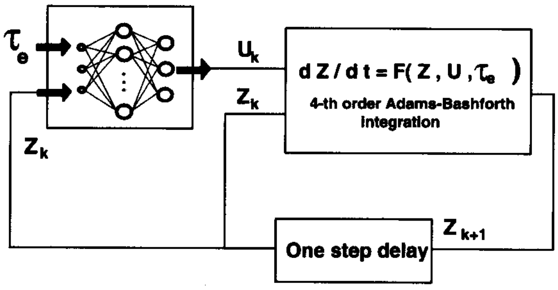

Fig. 1 Closed loop RBNN-dynamical system configuration.

We present an illustrative example of the results obtained after the neural network training for the case in which the energy confinement time of the device follows now a particular behaviour; with this purpose we use the following ELMy scaling law [9],

$$\tau_{elmy} = 0.029 I^{0.90} R^{2.03} B^{0.20} M^{0.2} \varepsilon^{0.19} \kappa^{0.08} n_e^{0.40} \mathrm{P}_{net}^{-0.66}; \quad (5)$$

where n_e and P_{net}, the electron density and the total net plasma heating into the system respectively, will be considered the only varying parameters in this expression.

A typical transient behaviour obtained using the resulting RBNN with the initial state $n_e = 0.90 \times n_0$, $f_\alpha = 0.90 \times f_0$, and $T = 1.10 \times T_0$, will be shown here. The energy confinement time used in the dynamical equations was obtained from τ_{elmy} in Eq. (5); however, in order to simulate measurements errors or a noisy enviroment, the value of τ_E fed into the network was determined through a Gaussian stochastic process with mean value given by the instantaneous value of τ_{elmy} and standard deviation $0.04 \times \tau_{elmy}$. Figure 2 shows the energy confinement time corrupted with noise which was fed into the network as function of time; and Figs. 3 and 4 show, respectively, the resulting time behaviour of the control variables S_f, S_α, and P_{aux}, and the state variables n_e, f_α and T, for this particular transient. In these figures the state and control variables are shown normalized to their nominal operating values and to their upper allowable limits, respectively. It is observed that in spite of the noise present in τ_E and therefore of the noisy action of the control variables, the network was able to succefully suppress these perturbations

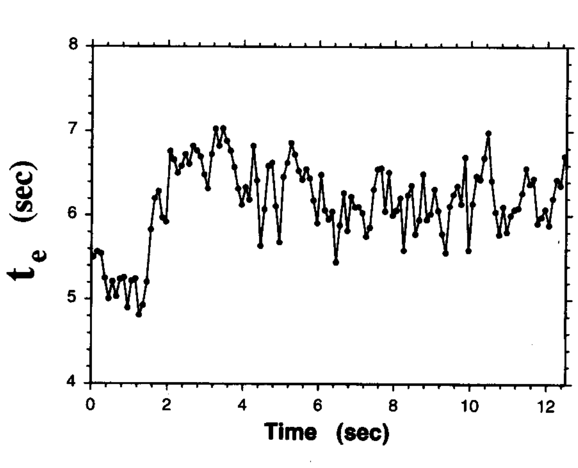

Fig. 2 Behaviour of the ELMy energy confinement time corrupted with Gaussian noise as function of time.

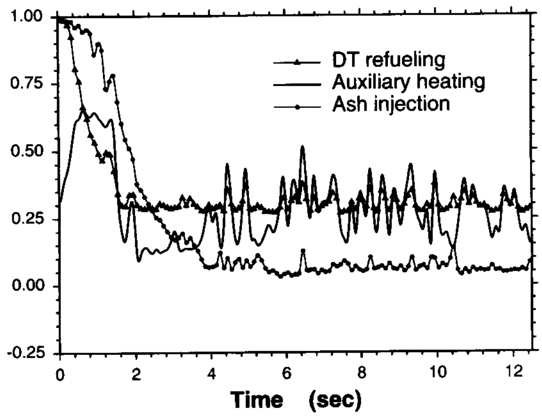

Fig. 3 Time behaviour of the normalized control variables produced by the RBNN, normalized to their maximum allowable values.

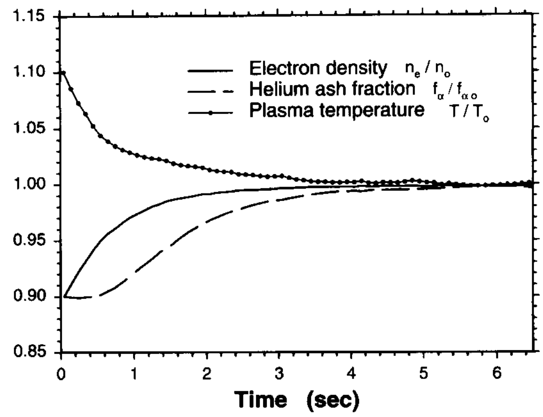

Fig. 4 Behavior of the normalized electron density, helium ash fraction and plasma temperature as function of time.

returning the system to a small neighborhood around the nominal operating point, within 6 seconds into the transient.

As it can be noted, the initial values used for the above transient lie outside the range used for training the network, which shows the generalization capabilities of the RBNN. Other simulated transients present a similar behaviour as long as the energy confinement time and the state variables do not get too far off the range of values used in the training session.

4. Conclusions

It is shown in this work that robust burn control in long pulse operations of thermonuclear reactors can be achieved with radial basis neural networks. In addition to the electron density, the fraction of helium ash and the plasma temperature, the input to the network also contains the instantaneous value of the energy confinement time. The control variables consist in the concurrent modulation of the DT refueling rate, the injection of a neutral He-4 beam and an auxiliary heating power. As a result of the training strategy for the network which consisted in keeping constant the value of the energy confinement time for the entire duration of each of the simulated transients, the resulting RBNN can succesfully stabilize the system regardless of any particular scaling law. A numerically simulated transient is used to show the capabilities of the resulting network, when the reactor follows an ELMy scaling law corrupted with Gaussian noise.

A complete research report is being prepared which includes details regarding the RBNN training and robustness tests with respect to the alpha particles thermalization time. Research activities are under way to allow also for the possibility that the D-T and alpha particles confinement times vary independently of τ_E.

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