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# Analysis of Self-Organizing Phenomena in Plasma Focus: Neural Network Approach

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**Abstract**

This paper describes application of artificial neural networks to investigation of the self-organizing phenomena in Plasma focus experiment, by means of analysis of magnetic field signals. We used back-propagation neural network, trained as the nonlinear predictor, as a tool to prove deterministic nature of plasma focus magnetic field signals.

**Keywords:**
plasma focus, self-organizing phenomena, nonlinear modeling

## 1. Introduction

This paper describes application of artificial neural networks to analysis of experimental data in our Plasma focus experiment.

The plasma focus chamber is the Mather type [1] and consists of two brass coaxial electrodes. Outer electrode consists of 18 cylindrically positioned brass roads. Capacitor bank of 45 $\mu$F is designed to be charged up to 40 kV. It is realized by means of 9 parallel connected capacitors, each of 5 $\mu$F. Electrical connections between capacitors themselves and between capacitor bank and plasma focus chamber are made of brass parallel plates.

Typical plasma focus current waveform is shown in Fig. 1. Values of circuit parameters imply that it is not possible to have such disturbances of plasma focus current, as oscillograms show. For measuring the plasma focus current we used a probe, realized as a linear section of the Rogowski coil, placed between the power transmission plates. Because our current probe essentially measures variations of magnetic field, we concluded that disturbances seen on plasma focus current waveform are electromagnetic interferences, picked by current probe.

Results of all our experiments show that there is a correlation between Electromagnetic Interference (EMI) pulse added on plasma focus current signal and neutron yield. We conducted the spectrum estimation of EMI pulse added on plasma focus current and plasma focus magnetic field signals [2]. Investigation of spectral characteristics of plasma focus current and plasma focus

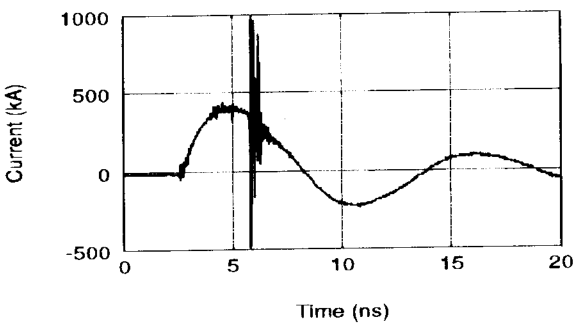


Fig. 1 Plasma focus current signal.

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magnetic field signals revealed chaotic nature of magnetic field signals and implied self-organization phenomena in focused plasma. Analysis confirmed that processes in plasma, which lead to nuclear processes, should be analyzed from nonlinear dynamics point of view. Because of highly pronounced nonlinear mode of operation of plasma focus device, we used artificial neural networks as a tool for analysis [3,4] and modeling [4] of magnetic field signals.

In our earlier experiments [2] we used transducer for measuring magnetic field identical to our current probe, but placed outside of the power plates. Interferences from both transducers were very similar, confirming our hypothesis that disturbances seen on plasma focus current waveform are electromagnetic interferences. In this paper presented are results of our most recent experiments. Magnetic field probe is located at radial distance $r = 30$ mm from the outer electrode, and at height $z = 0$ mm from the muzzle end.

## 2. Predictive Modeling of the Plasma Focus Magnetic Field Signals Using Neural Networks

Artificial neural networks have been successfully applied to many areas of nuclear science [5]. Most of the neural networks used in these applications are back-propagation or radial-basis neural networks [5,6], which associate relations between inputs and outputs by using weight coefficients. In analysis, presented here, we used back-propagation neural networks.

The main problem in analysis of plasma focus magnetic field signals is the fact that they are non-stationary, and of very short duration. Furthermore, they are acquired in a very noisy conditions, including the 8 bit A/D converter noise. So, embedding dimension and time delay, needed for attractor reconstruction [7] could be determined only approximately, with the high probability of the erroneous result. However, this is the kind of a problem, where using of the neural networks is most advantageous.

Neural networks provide a nonparametric approach for the nonlinear estimation of data. During a training session free parameters of neural network (synaptic weights and biases) are adjusted in a systematic way as to minimize a cost function. The neural network learns from examples by constructing an input-output mapping for the problem to be solved. In this paper, neural network, trained as the nonlinear predictor [5,6], is used as a tool to prove deterministic nature of the plasma focus magnetic field signals.

For the predictive modeling of the plasma focus magnetic field signals we used a multilayer perceptron trained with the backpropagation algorithm. The general structure of the neural network nonlinear predictor model is shown in Fig. 2. Training of the neural network is obtained by T position of a switch. A set of $p$ samples $x_{n-1}$, $x_{n-2}$, .., $x_{n-p}$ is applied to the input layer of the network, and its synaptic weights are adjusted to minimize the prediction error (i.e. the difference between the actual sample value $x_n$ and the predicted value, $x_n^p$ in a mean-square sense. The training set should be large enough, and the training session has to be continued untill synaptic weights of the network reach steady-state values.

Predictive mode of operation is obtained by P position of the switch. The network is initialized by presenting it a set of samples $x_1$, ..$x_{p-1}$, outside of the training set. The resulting prediction is delayed by one time unit and then fed back to the input. Correspondingly, all samples are shifted by one time unit, and the oldest sample $x_1$ is dropped to make room for the delayed prediction $x_n^p$. The new prediction is made using the newly formed input to the neural network, and the process is repeated until all the original samples have been removed. After that, the neural network should produce a time series that is representative of the dynamics of the plasma focus magnetic field signals.

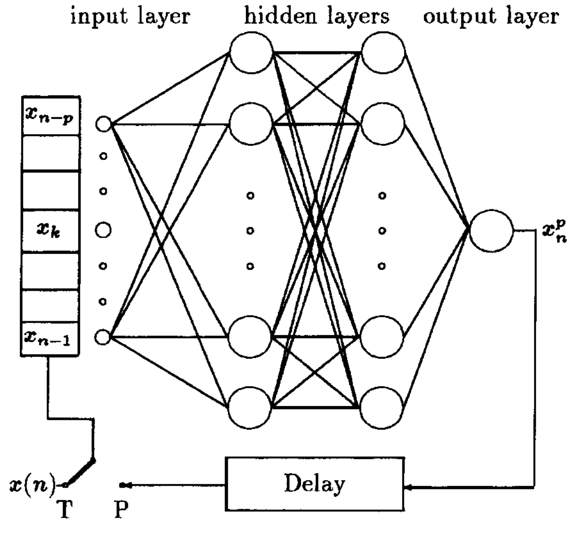


Fig. 2 Recursive predictor using neural network. $x(n)$ denotes discrete sequence, $x_n$ is the n'th element of the sequence, $x_n^p$ is the predicted value of the $x_n$.

## 3. Analysis of Experimental Data

Plasma focus magnetic field signal corresponding to the pinch in deuterium is shown (solid curve) in Fig. 3. The signal is very similar in appearence to the zoomed part of the interference seen on the plasma focus current signal. Signals corresponding to the pinch in hydrogen are of similar appearance, usually of slightly smaller amplitude. The signals are acquired with the sampling rate of 1GSamle/s, so, in the following text, one point of discrete sequence corresponds to 1 ns.

The size of the input layer of the neural network used for the predictive modeling should be chosen in accordance with the formula $p \geq \tau D_E$, where $D_E$ is the embedding dimension and $\tau$ is normalized time delay [5]. It should be noted that, if $p$ is chosen much larger than the $\tau D_E$, the contaminating effects of additive noise become more pronounced. Our initial estimation was $D_E = 10$ and $\tau = 5$. However, because of uncertainty of estimation of $p$, we varied parameters of the neural network, i.e. number of neurons and number of layers, seeking for the optimal configuration.

We obtained the best results using a neural network which has 60 nodes in input layer. This confirms that our initial estimations ($D_E = 10$ and $\tau = 5$), which correspond to $p = 50$, are not far from correct. We tried simulations with the one and with two hidden layers. Better results were obtained with the two hidden layers. Each of hidden layers has 100 neurons, which, again, was determined by varying the number of neurons. Predicted value of $x_n$ is obtained by a linear output neuron.

It should be mentioned that convergence of the training session was very dependent on the initial values of synaptic weights. Also, the convergence of the training session was sensitive to the choice of the begining and the end of the sections of magnetic field signals, used to form the training set. As the number of "intuitive" modifications of the parameters of the neural network in our simulation experiments slowly but inevitably grew, it became obvious that in our future simulation experiments the genetic algorithms should be used for optimization of the structure of the neural network predictors.

Figures 3 and 4 show results of recursive prediction of magnetic fields signals. We see on Fig. 3, (where $p = 60$), that for about the first 60 points, the predicted and actual waveforms match fairly closely and thereafter they diverge. Fig. 4 shows recursive prediction, when number of input neurons is too small, so the model fails to capture the dynamics of the signal ($p = 40$). This results confirm that magnetic field signals are locally predictable. The horizon of predictability for these signals is about 60, which for used sampling time of 1 ns corresponds to 60 ns. The same neural network was trained on samples from signals corresponding to pinch in deuterium and hydrogen. Predictions for both types of signals are equally good, which shows that both signals are of the same nature.

## 4. Conclusion

Our model using neural network trained as the nonlinear predictor proved that magnetic field signals corresponding to the pinch in deuterium and hydrogen are deterministic, both of the same nature. For the used sampling rate, the horizon of predictability for these signals is about 60. In our future simulation experiments, the genetic algorithms should be used for

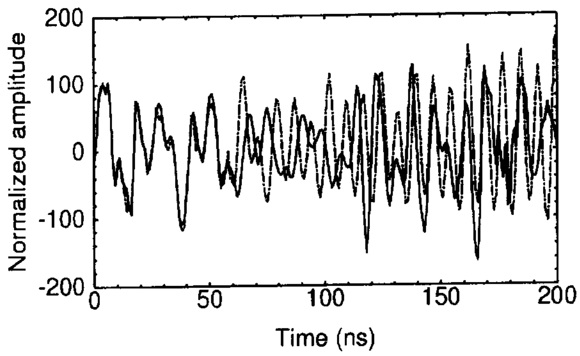


Fig. 3 Neural network prediction (dash-dotted curve) of the plasma focus magnetic signal (solid curve), using neural network with input layer of $p = 60$ nodes. First 60 points, used for initialization of the predictor, are not shown.

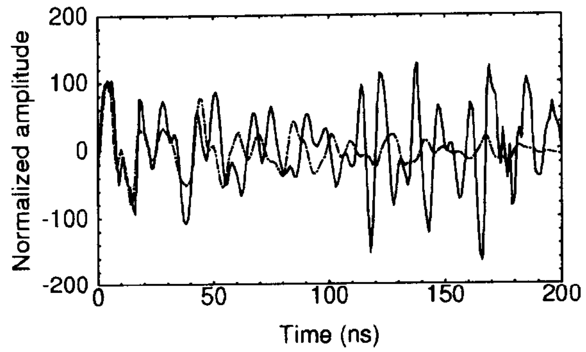


Fig. 4 Neural network prediction, using neural network with too small input layer ($p = 40$).

optimization of the structure of the neural network predictors.

## Acknowledgment

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