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** See annex of M.L. Watkins et al, "Overview of JET Results",*
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ABSTRACT
It has been demonstrated that kernel machines, like Multilayer Perceptron (MLP) networks, are able to classify any set of patterns defined in real domains [1]. They can also determine the relationship occurring among the input signals, provided that a very large number of hidden neurons is included. Unfortunately this leads to a tradeoff in terms of computational resources, since the bigger is the size of the net the longer is the time needed to re-train it. This poses a problem in Magnetic Confinement Fusion devices like JET, where different operating scenarios have to be explored, requiring periodic retraining of the nets. Moreover, too complex MLP networks can be difficult to interpret and present lower generalization potential.

This paper presents a new approach based on hybrid Geometrical Kernel Machines, used as regressors, to provide a functional relationship among the input variables. The particular application described is the transition between the L and H modes of confinement, with the aim of deriving a data-driven functional expression for the L-H threshold to be used for both prediction and interpretation

1. INTRODUCTION
In the last decades, real time control has assumed an increasingly important role in experimental fusion devices. Since the plasma scenarios are becoming more complex, with higher shaping and input power, feedback on various parameters is necessary to stabilize the configurations and to maximize performance [2]. Although a large number of real time applications used to identify the plasma state are present at JET [3,4], all of them work with pre-programmed discharge parameters. Therefore, in case of unexpected variation of the plasma state, the real time controller can behave nonoptimally and lead the plasma to a region of the operational space far from the one of best performance [5].

The tokamak is the primary device which has the potential for achieving thermonuclear fusion in a controlled environment. Improved modes of confinement have been found which have important implications in the design of fusion reactors. In a tokamak heated by a neutral beam, the preliminary results were not satisfactory; it was observed that as the neutral beam power was increased, the particle and energy confinement times decreased. This operation regime of the tokamak is known as the Low (L) mode of confinement, whereas the High (H) mode is reached with a further increase in input power up to a point where the discharge makes a dramatic transition to a good confinement mode.

The Low to High confinement (L-H) transition in tokamaks was first observed over twenty years ago in the ASDEX device [6, 7] and is a remarkable self-organization phenomenon in tokamak plasmas [8]. Although many theories for the L-H transition have been developed [9], the basic mechanism of this phenomenon is not fully understood yet because it depends on several variables, interacting in a highly non-linear way.

As already mentioned, a MLP neural network presents a chance to approximate any kind of multi-variables function, provided that a large number of neurons is present in the hidden layer. In fact, as reported in [10], a single layer network with *n+1* hidden neurons is able to learn *n+1* distinct samples with zero errors. This is acceptable for small input sets, but in the case of large databases like in JET, where signals can be sampled at kHz rates for several seconds, it means long re-training times when new patterns have to be added to the training set. This can lead to a slow and not prompt answer of the real time predictor. Moreover, a very high number of neurons makes it very difficult, if not impossible, to derive any information about the studied phenomenon from the topology of the network, something that could be useful to make progress in some aspects of plasma physics relevant to Nuclear Fusion.

The purpose of the approach showed in the present paper is aimed at overcoming this drawback. A MLP with a single hidden layer is geometrically built, see Fig.1, and the resulting network is able to give a non-linear functional relationship among patterns defined in the real domain. The proposed procedure is based on a feedback algorithm that allows determining both the number of neurons and the synaptic weights of networks with a single hidden layer. The approach gives the opportunity to select the complexity level of the final network. The best tradeoff between accuracy and computational load can therefore be chosen.

The algorithm is based on the principle of adaptive filtering, where the filter modifies its architecture and coefficients, customizing them on the base of the incoming signals and the operating environment. In the approach presented in [11] the net is automatically built by the algorithm performing a separation of the input set in groups, enveloped by convex polyhedrons (Fig. 2), by means of linear hyperplanes. In the network, each neuron represents a linear separator and the connection weights converging on a neuron are the coefficients of the corresponding linear hyperplane.

In the case of the L-H transition of Tokamaks a linear separation is too restrictive, but we can use the same approach to build the net, but, instead of separating groups belonging to different classes, the separation is between samples belonging to a certain time-window and the remaining others.

The separation is not more provided by linear hyperplanes but by means of concave polyhedrons, see Fig. 3.

In Fig. 3 the samples are enveloped by a polytope that identifies a convex polyhedron represented by the facets {a, b, c, d, e, f}. Those facets can also be characterized by a set of linear inequalities. By means of those inequalities, all and only the samples belonging to the same group are included and hence enveloped. The outer samples are called vertexes.

As said above, this kind of enveloping is too restrictive then we need to identify a so called *concave polyhedron*: other than respecting the constraint of the facets {a, b, c, d, e, f} a sample can be included by the new polyhedron if it respects at least one between $\{f_1, f_2\}$ and one between $\{d_1, d_2\}$. The coefficients of the linear inequalities representing those new facets are the synaptic weights of the neurons between the input and hidden layer.

The activation function for the hidden layer is a sigmoid. The weights of the second connection layer are evaluated projecting the enveloped groups in a feature space where the coordinate are calculated combining the sigmoids related to the same concave polyhedron.

RESULTS

According to [2], a set of 7 diagnostic signals related to the pulse range Pulse No's: 55859-59424 has been chosen to describe the plasma regime during the L-H transition. The chosen pulses were considered by various experts of JET team to evaluate the correct LH transition time. 70% of the pulses have been used to build and train the net, whereas 15% have been used to test it and the remaining 15% for the validation procedure. Moreover, the plasma parameters used for the analysis described in this paper are the following: the plasma current (I_p), the beta normalized (Bn), the safety factor (Q_{95}), the plasma density (Dens1), the Magneto-HydroDynamic energy (WMHD), the $D\alpha_{outer}$ spectrum integral (FFTamplitude_O) and the $D\alpha_{inner}$ spectrum integral (FFTamplitude_I). The network obtained from the algorithm is constituted of 7 input neurons, 21 hidden neurons and 1 output neuron, the equation coming out from the combination of the sigmoids is of the form:

$$z(x_1, x_2, ... x_N) = \beta + \sigma_1 \left(\frac{1}{1 + e^{-\alpha_1 x}} \right) \sigma_2 \left(\frac{1}{1 \quad e^{-\alpha_2 x}} \right) \sigma_3 \left(\frac{1}{1 \quad e^{-\alpha_3 x}} \right) .....\sigma_N \left(\frac{1}{1 \quad e^{-\alpha_N x}} \right) \qquad (1)$$

The eq. [1] has been applied to the test set providing a test rate of 35%; that means it is able to recognize with a reasonable success rate the L/H transition.

CONCLUSIONS

In this paper, a new strategy to build an optimal MLP neural network to be used as non-linear regressor has been presented. The algorithm works as a sort of adaptive filtering and the derived net is able to give a reasonable relationship between the input variables for the case of the L-H transition. Further studies are under way to investigate the application of this approach to the developments of predictors. Moreover the first attempts are also being performed to interpret the topology of the network to derive physical information about the physics of the L-H transition.

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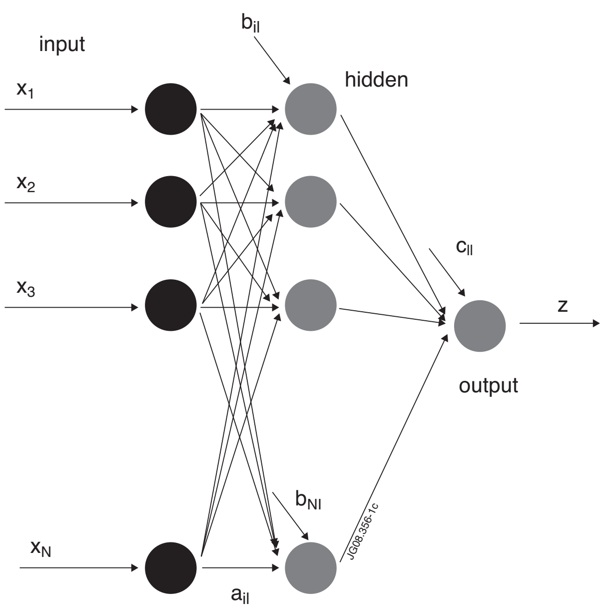

Figure 1: Topology of a MLP neural network with a single hidden layer.

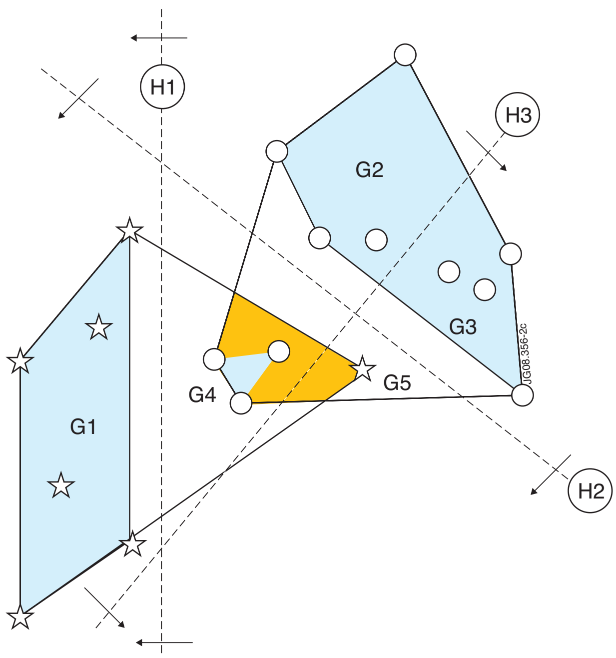

Figure 2: groups and linear hyperplanes, courtesy of [11].

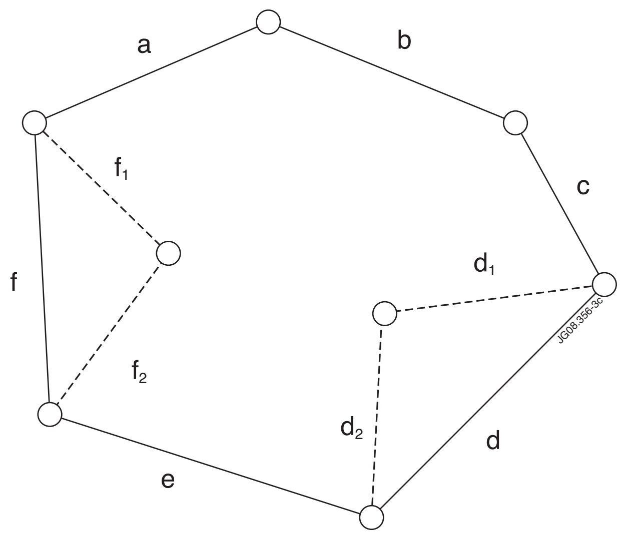

Figure 3: convex and concave enveloping