Prospects of Real-Time Ion Temperature and Rotation Profiles based on Neural-Network Charge Exchange Analysis.

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INTRODUCTION. A neural network technique used at JET to extract plasma parameters like ion temperature, rotation velocities or spectral line intensities from charge exchange (CX) spectra is described. Based on earlier proof-of-principle results /1/ on the application of neural nets for the analysis of complex spectra such as the HeII (n=4 to n=3) spectrum, the options for a real-time analysis of complete radial profiles using the simpler C VI CX-spectrum with fewer components are addressed. A similar attempt has recently been undertaken at DIIID /2/. Usually spectra are analysed by fitting Gaussian line shapes to all observed spectral components using a least squares algorithm. The least-squares technique is a well advanced and established procedure providing high accuracy and error estimates It is, however, extremely time consuming (>200 ms/spectrum) and human interaction is often required to provide appropriate initial guesses. In this paper it is shown that in the case of the C VI CX spectra, neural networks can give a good estimation (better than ±20 % accuracy) for the main plasma parameters (T_i, v_{rot}). Since the neural networks approach involves no iterations or initial guesses the speed with which a spectrum is processed is so high (0.2 ms/spectrum) that real time analysis will be achieved in the near future.

THE C VI SPECTRUM. Fig. 1 shows a typical example of a C VI CX spectrum that a neural network has been trained to analyse. The spectrum consists of three different spectral lines. The Be II line is excited by electron collisions and originates from areas just outside the separatrix. The active C VI charge exchange line is emitted from the intersection volume of the neutral beam and the viewing line, while the passive C VI charge exchange emission line is produced just inside the separatrix by reactions with

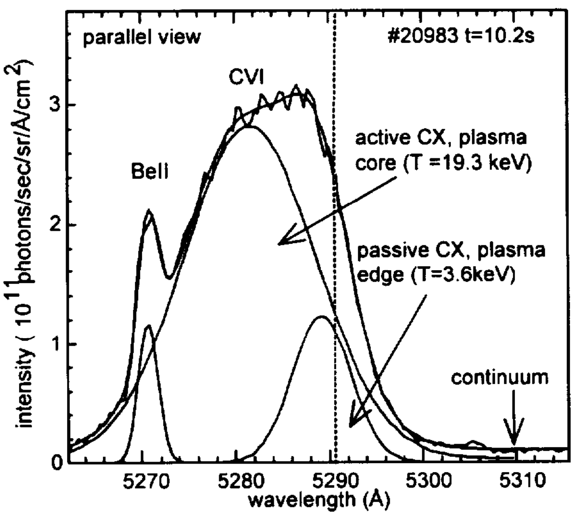


Fig. 1 C VI charge exchange spectrum showing all its individual components

recycling neutral hydrogen. Due to the toroidal rotation of the plasma, the active as well as the passive CX lines are shifted relative to their nominal wavelength position. This means, if one disregards the continuum level (since it can be determined separately from a line free part of the spectrum), 9 fit-parameters are required to describe such a spectrum by 3 Gaussians. The ion temperature is derived from the width of the spectral lines. Since experiments have shown that the Be II ions do not rotate with the plasma, the toroidal rotation velocity is derived from the shift of the active CX line relative to the Be II line.

THE CHARGE EXCHANGE SPECTROSCOPY NEURAL NETWORK. A back-propagation neural network simulation program has been developed on an IBM-PC in C++ which runs under Windows. For the back-propagation algorithms a commercial library /3/ was used which could be used together with a Digital Signal Processor (DSP) board for the PC. The DSP board reduced the training time by a factor 12; a significant gain considering that training often takes several hours. The PC program automatically produces a FORTRAN subroutine for the forward code, which can easily be transferred to the IBM mainframe and implemented in the standard analysis codes. In order not to produce a look-up table, but to make a neural network with a good generalisation ability, two data sets have always been used, a training set and a test data set, which had a size of about 10% of that of the training set. Moreover the training was always stopped whenever the error of the test set started to increase, which is the point when the network starts to memorise insignificant features of the training set. This status is usually achieved after a few hundred epochs or 1 to 3 hours. However, good accuracy is already reached after about 1/3 of this time (fig. 2). To achieve a good generalisation ability a neural network should always have as few neurons in the hidden layers as possible. As a rule of thumb it was assumed that the number of hidden neurons should be approximately equal to the number of fit-parameters needed to describe a spectrum. Practical tests revealed that 7 hidden neurons were sufficient for the C VI spectrum. All networks trained had 298 input neurons, one for each pixel in the

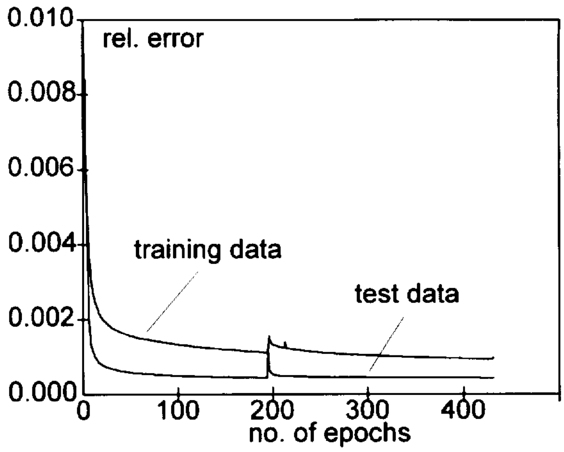


Fig.2: Error of the training (13315 spectra) and test data set (1492 spectra) of the ion temperature network.

spectrum, and only one output neuron representing ion temperature, rotation velocity or line intensity respectively (fig. 3). It appeared that having only one output neuron made it considerably easier (reduced convergence time) for the network to learn, compared to a network with 3 or more parameters as output. It also simplified the decision of when the network had the best generalisation ability for the different parameters.

CONCLUSIONS AND FUTURE PROSPECTS. The neural network was tested on 30000 spectra, selected from a widely changing range of core and edge plasma conditions (i.e. 1 keV<T_i<25 keV, 10^{17} m^{-3}<$n_{C\ VI}$ <2 10^{18} m^{-3}). Over 80 % of the neural network results are within 20 % of the more accurate least-square results (fig. 4) showing that the feed forward neural network can be an efficient tool with a wide range of applications. However, a substantial number of training spectra is required to train a network. A set of 13000 training spectra and 1500 test spectra has been used. Presently the neural network is used to provide reliable initial estimates for the least square fitting routine and for immediate analysis in-between shots.

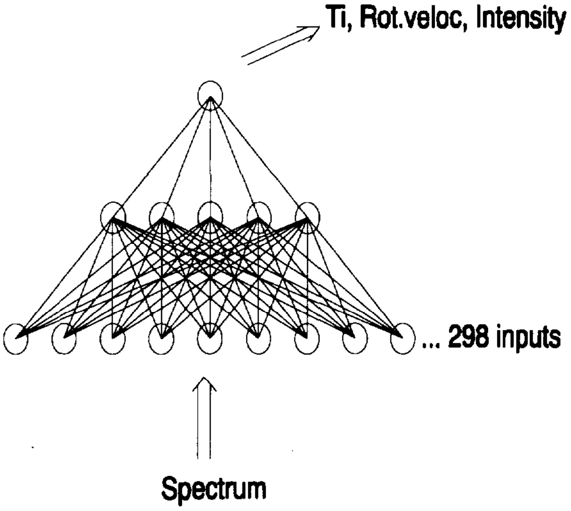


Fig. 3 Basic structure of the neural net used. The number of hidden layer neurons varied

In fig. 5-8 some examples are given which show the typical quality of neural network based ion temperature analysis. It is expected that it will also be possible to provide real-time ion temperature and plasma rotation profiles in the control room, which in the near future can for example be used as input for plasma stability control (rotation frequency) or as feed back signal (ion temperature) enabling burn-control studies for applications in Next-Step machines. In order to improve the training

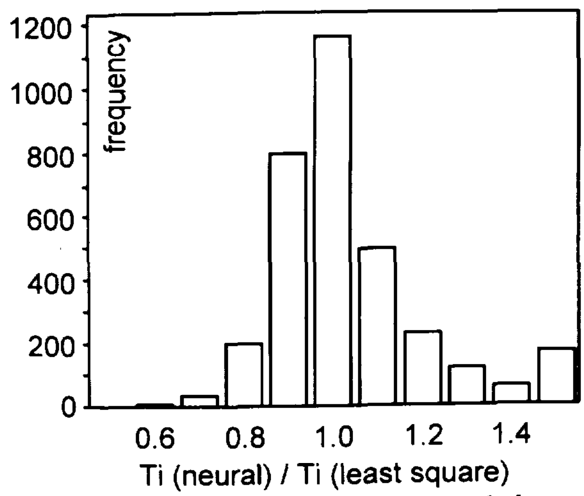


Fig.4Ratio of neural network and least-square solutions for the ion temperature of 3000 test spectra taken at R=3.4 m The values at 0.5 and 1.5 are the sum of all values further out on each side.

algorithm it is planned to introduce, in a next step, a method to dynamically change the momentum and learning coefficient and also to implement the conjugate gradient method, which is believed to be an order of magnitude faster than the ordinary back-propagation method. On the input side the pre-processing of the data will be improved. Moreover an attempt will be made to use Bayesian methods ,which have only recently been developed for back-propagation networks /4/, to choose network parameters (such as the number of hidden neurons) and to determine the errors of neural network estimations.

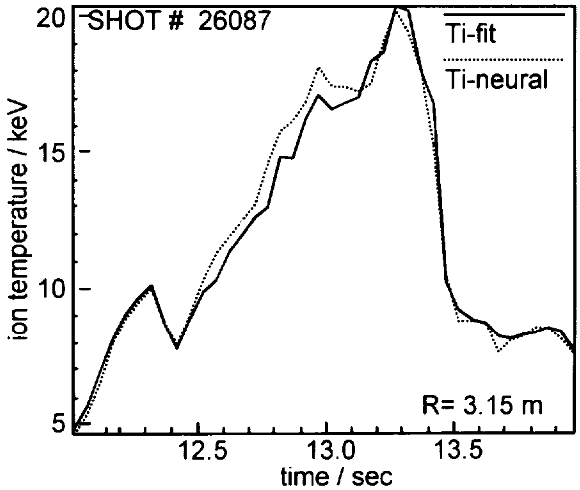


Fig. 5: Ion temperature time trace for a case where the temperatures reach the extremes of the training set.

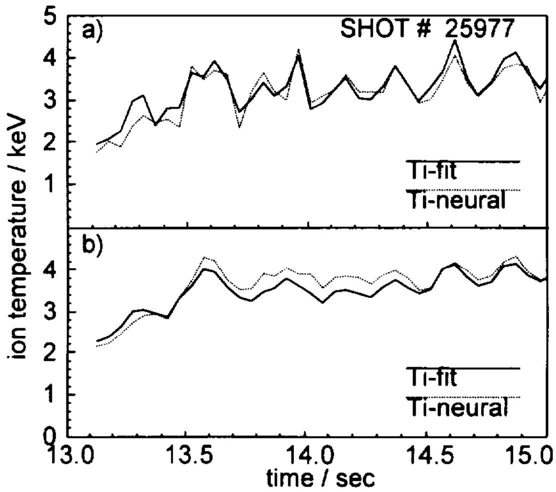
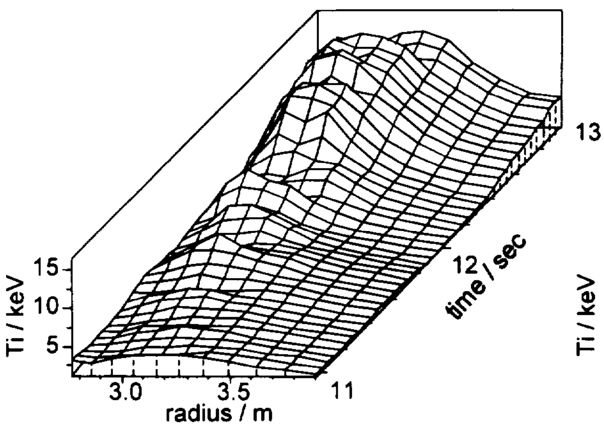


Fig. 6: Ion temperature sawteeth resolved by the neural net. In a) the spectra were analysed without averaging, while in b) the spectra were averaged over 3 frames prior to analysis.



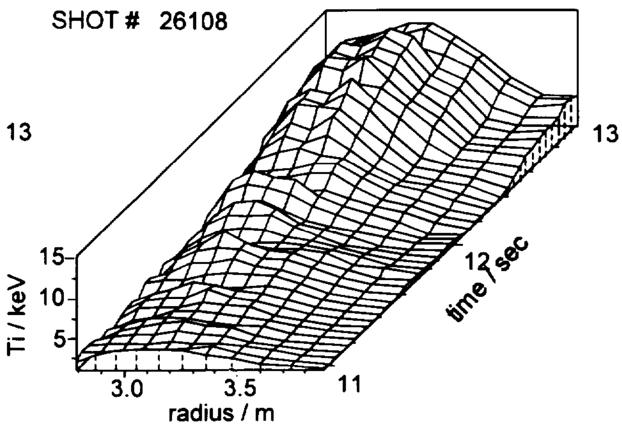


Fig. 7: Least-square fit ion temperature profile.

Fig. 8: Neural network ion temperature profile.

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/3/ Neural Net Inc.
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