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TRANSPORT IDENTIFICATION BY NEURAL NETWORK IN JET ITB REGIMES

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Introduction

Many efforts have been dedicated to establish, by fitting a large number of experimental data, zero-dimensional scaling laws for conventional scenarios to give global information on transport. Despite its advantages in designing future devices, this approach is not suitable to investigate transport phenomena in advanced scenarios. The present work focuses on the local thermal energy transport in JET discharges with and without ITBs. The aim is twofold: (i) to exhibit the dependencies of the heat diffusivity on local dimensionless parameters which seem to be relevant from a theoretical basis and (ii) to propose a purely empirical approach for predictive transport modelling. Neural networks will be introduced as an appropriate tool to handle such a problem and provide an alternative approach to previous attempts of approximating semi-empirically the experimental heat diffusivity function.

The first section describes the database which has been built for the analyses, then presents a correlation study between the experimental diffusivities and some dimensionless quantities deduced from the turbulence theory. In the second section, we show the heat diffusivity functions given by a neural network trained with data in anomalous transport regime and discuss their relevance to the expected theoretical results. The third section tests our technique as a predictive transport tool, and finally some potential applications are briefly proposed in the last section.

1. Correlation analysis of the heat diffusivities

A set of 20 discharges, with and without an ITB, with either monotonic or reversed shear q-profiles has been selected from the JET database. In these experiments, described in [1], the injected torque has been varied systematically by combinations of tangential bank beam, normal bank beam and on-axis ion cyclotron heating (at B_ϕ=2.6T and I_p=2.2-2.3MA). Hollow q-profiles have been obtained by coupling 2MW of LHCD during the current ramp-up phase. Only the main heating phase, after the end of the LHCD prelude, has been considered in our analysis. The power depositions of ICRH were determined by the code PION, with the NBI source rates calculated with PENCIL. All the other data were taken from the experimental measurements, and the current density profile was given by the magnetic reconstruction code EFIT constrained by infrared polarimetry data. The diffusivities were deduced from a power balance analysis performed by the transport code ASTRA [2] in the region of $0.1<r/a<0.8$. In this work, we focus on the electron heat diffusivities because they can be evaluated more accurately thanks to the high space-time resolution of the ECE diagnostic. In total, 13817 and 446 electron heat diffusivities were computed outside and inside ITB, respectively. The ITBs were characterised by the ρ_T* criterion [3].

We have firstly carried out a correlation analysis between the electron heat diffusivities χ_e and the following dimensionless quantities: $\rho_{Te}{}^*=\rho_s/L_{Te}$, $A_{Te}=R/L_{Te}$, $A_{ne}=R/L_{ne}$, s, q, $\tau=T_i/T_e$

and $M_\phi=v_\phi/c_s$. Normalised diffusivities have been also considered, namely χ_e/χ_{Bohm} and $\chi_e/\chi_{gyroBohm}$, where $\chi_{Bohm}\propto T_e/B_\phi$ is the so-called Bohm diffusivity and $\chi_{gyroBohm}=\rho^*\chi_{Bohm}$ the gyroBohm one. The correlation factor Σ_{xy} between two variables x and y is defined by

$$\Sigma_{xy}=\frac{E\left[(x-\bar{x})(y-\bar{y})\right]}{\sqrt{E\left[(x-\bar{x})^2\right]E\left[(y-\bar{y})^2\right]}}$$

where E[…] denotes the expectation value, $\bar{x}$ and $\bar{y}$ the mean values of x and y. A correlation factor of 0 means that x and y are independent, and a factor of 1 indicates a purely proportional relation $y\propto x$.

Figure 1 shows a diagram of the correlation factors between χ_e, χ_e/χ_{Bohm} or $\chi_e/\chi_{gyroBohm}$, and the dimensionless quantities - ρ_{Te}^*, A_{Te}, A_{ne} … - outside and inside ITB. Outside ITB, it can be seen that the selected set of parameters is globally more correlated to $\chi_e/\chi_{gyroBohm}$ - or

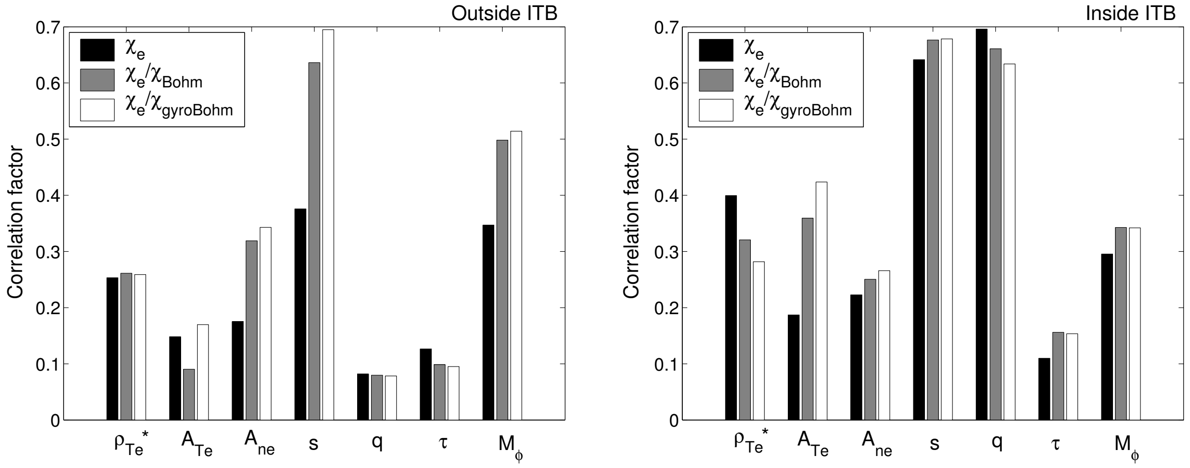

***Figure 1** — a) (left) Correlation factor between the electron heat diffusivity or its normalised derivatives and some theory-relevant dimensionless outside ITB. b) (right) The same but inside an ITB. $0\leq\rho_{Te}^*\leq0.02$, $0\leq A_{Te}\leq15$, $0\leq A_{ne}\leq8$, $-1\leq s\leq1.5$, $1.2\leq q\leq3.8$, $0.3\leq\tau\leq1.8$, $0.05\leq M_\phi\leq0.6$.*

even χ_e/χ_{Bohm} - which means the diffusivity function is "closer" to the following form: $\chi_e=\chi_{gyroBohm}f(…)$ where f is an unknown function of our dimensionless parameters; no clear conclusion can be drawn from the results inside ITB. The dependency of the magnetic shear is quite strong in the two cases as foreseen by the microturbulence theory. On the contrary, the safety factor does not seem to change the electron transport level outside ITB whereas it clearly plays a role inside, possibly through the mechanism of rational q-values in ITB triggering [4]. The ratio of electron and ion temperature τ has a weak effect on electron diffusivities as proved by a correlation factor always lower than 0.17. To identify properly the dependencies, the dimensionless variables must be as much as possible independent of each other. It was seen that ρ_{Te}^* and A_{Te} in one hand, M_ϕ and τ in the other hand, are correlated with correlation factors up to 0.76 and 0.92 respectively. The rest can be considered decorrelated since the correlation factors do not exceed 0.46. As a result, the electron heat diffusivity may be written as

$$\chi_e=\chi_{gyroBohm}f\left(A_{Te},A_{ne},s,q,\tau\right) \quad (1)$$

at least outside ITB.

2. Approximation of the electron heat diffusivity function

Let us assume that a non-linear multivariate function exists which describes transport in tokamak plasmas and that this transport is purely diffusive. The above correlation analysis suggests an electron heat diffusivity of the form (1) whose function f is unknown. Its approximation from experimental data demands to overcome three difficulties: (i) the non-linear multivariate nature of the function, (ii) for a given experiment, all the parameters vary at a time and (iii) the uncertainties of data. Neural network appears to be an ideal tool to handle such a problem because according to the universal approximation theorem it can approximate any non-linear multivariate function to an arbitrary accuracy [5]. Hence, we have carried out a two-layer neural network with 5 neurons on the first layer and with a pure linear transfer function. The training was performed by a Levenberg-Marquardt algorithm [6] with (A_{Te},A_{ne},s,q,τ) as input and log($\chi_e/\chi_{gyroBohm}$) as output outside ITB. Among the 13817 data collected for the correlation analysis, 4000 were randomly chosen for training the network. Its robustness has then been assessed by simulating the whole database and comparing the output with the experimental diffusivities: a correlation factor of 0.87 was obtained, which allows a satisfactory approximation while avoiding to overfit the data.

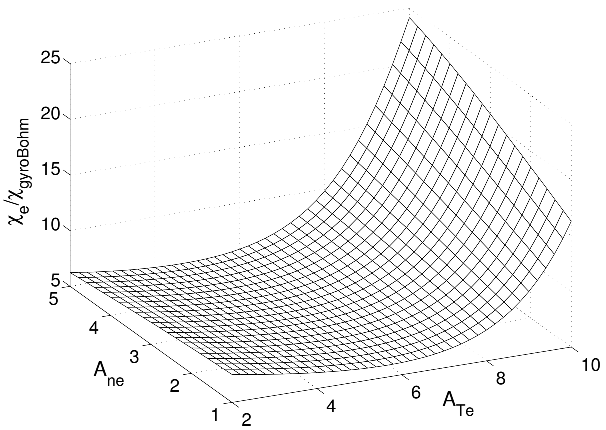

***Figure 2 -** $\chi_e/\chi_{gyroBohm}$ as a function of A_{Te} and A_{ne} after the neural network. s=-0.5, q=2, τ=1.*

Figure 2 shows the results of such a simulation where the dimensionless quantities s, q and τ were fixed. Clearly, the transport increases with the gradients. At a given normalised density gradient, $\chi_e/\chi_{gyroBohm}$ raises significantly over a normalised temperature gradient of $(R/L_{Te})_c \approx 7$-8, in qualitative agreement with the so-called critical temperature gradient; its expected value given by analytical approximations of ITG+TEM gyrokinetic simulations [7] is 8.35 in these conditions.

The variations of heat diffusivity with the magnetic shear are depicted on figure 3.

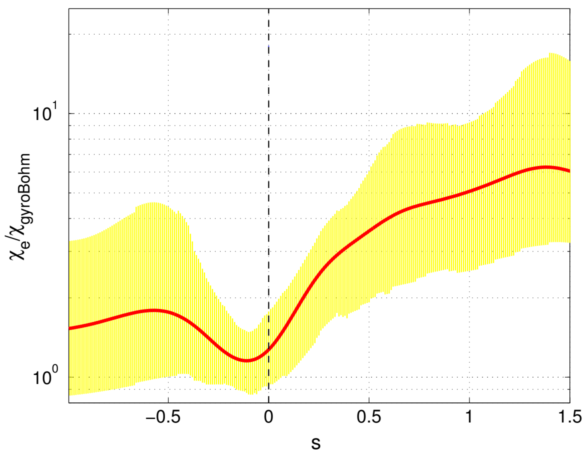

***Figure 3 -** $\chi_e/\chi_{gyroBohm}$ versus the magnetic shear given by the neural network. The shaded area stands for the 1-σ uncertainty of the approximation. A_{Te}=5, A_{ne}=3, q=2, τ=1.*

A strong reduction of the transport is observed in the region of negative magnetic shear, the lowest level being located close to s=0. The diffusivity raises dramatically with positive shear and seems to reach a maximal value at s≈1.4. The shaded area characterises the reliability of the approximation: it has been computed by training the neural network many times with various subsets of 4000 data taken randomly from the entire database, and by making a statistics on the resulting approximations. The area is then bounded by one standard deviation around the average approximation.

In agreement with the correlation analysis, it was seen that the dimensionless parameters q and τ hardly affect the transport although theories predict the stabilisation of ITG modes at large τ and a critical gradient temperature dependant of s/q.

3. Neural network transport prediction

We have attempted to apply the semi-empirical approach by neural network to transport modelling in ITB regime. After having trained a neural network on the entire database, the electron heat diffusivities have been computed for a JET ITB discharge not belonging to this database, and then compared with the diffusivities evaluated by ASTRA. The input parameters were ρ_{Te}*, A_{ne}, s, q, M_ϕ and the output parameter $\log(\chi_e)$. The small number of data inside ITB made the approximation difficult to fulfil within a transport barrier. The network tended to ignore the data with low diffusivities and thus it was not able to approximate satisfactorily the physics of improved transport. In order to increase the weight of these data in the training phase, we have repeated them several times in the database.

Figure 4 shows the comparison of electron heat diffusivity profiles between those evaluated by a power balance analysis with ASTRA and those predicted by the trained neural network. It can be seen a rather good agreement, at least in order of magnitude, even inside the ITB located around r/a=0.3. The transport at the edge is badly reproduced certainly due to the fact the network has ÔlearntÕ only the core physics (r/a<0.8). Therefore it cannot guess the edge transport, which involves specific mechanisms for instance linked to the interactions with the wall, and whose the input parameters take values out of the range of our database, e.g. high magnetic shear or very short gradient scale lengths.

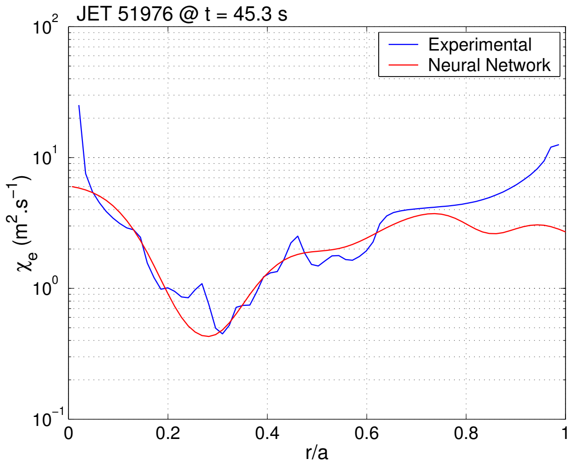

***Figure 4** — Comparison of experimental and predicted — by neural network - electron heat diffusivities for a JET pulse (#51976) at a time when an ITB is formed.*

4. Discussion

Facing the important issue of transport in tokamak plasmas, a technique to approximate the heat diffusivity function, both non-linear and multivariate in nature, from the experimental data has been proposed. Such a method may complete the purely theoretical approaches by suggesting any tendency or by supporting any numerical result. It could allow to perform in a more systematic way transport studies on large database like the international ITB database which groups together several devices [8].

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References

[1] C.D. Challis et al, to be published in Plasma Phys. Control. Fusion.
[2] G. Pereverzev and P.N. Yushmanov, IPP-Report 5/98, February 2002.
[3] G. Tresset et al, Nucl. Fusion, **42** (2002) 520.
[4] E. Joffrin et al, submitted to Plasma Phys. Control. Fusion.
[5] G. Cybenko, Math. Control Signals Systems, **2** (1989) 303.
[6] M.T. Hagan and M. Menhaj, IEEE Trans. Neural Networks, **5** (1994) 989.
[7] C. Fourment et al, to be submitted in Phys. Plasmas.
[8] G.T. Hoang et al, this conference.