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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.

I.   CORRELATION ANALYSIS OF THE HEAT DIFFUSIVITIES

A set of 20 discharges, forming or not 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 consistently with the NBI particle sources 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. Outside ITB, 13817 electron heat diffusivities have been computed, and 446 inside. The ITBs were characterised by the ρ_T* criterion [3].

We have firstly carried out a correlation analysis between the electron heat diffusivities ce and the following quantities: ρ_{Te}*=ρ_s/L_{Te}, A_{Te}=R/L_{Te}, A_{ne}=R/L_{ne},s, q, τ=T_i/T_e and M_ϕ=v_ϕ/c_s. Normalised diffusivities have been also considered, namely χ_e/χ_{Bohm} and χ_e/$\chi_{gyroBohm}$, where χ_{Bohm}∝T_e/B_ϕ is the so-called Bohm diffusivity and $\chi_{gyroBohm}$=ρ*χ_{Bohm} the gyroBohm one. The correlation factor Σxy between two variables x and y is defined by

$$\Sigma_{xy} = \frac{E\,[(x-\bar{x})(y-\bar{y})]}{\hat{}E\,[(x-\bar{x})^2]\,E\,[(y-\bar{y})^2]}$$

where E[ ] denotes the expectation value, x and y the mean values of x and y.

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 $\chi_e/\chi_{gyroBohm}$ — or even χ_e/χ_{Bohm} - is globally more correlated to the selected set of parameters, which means the diffusivity function is closer to the following form: $\chi_e = \chi_{gyroBohm}f(\rho_{Te}^*, A_{Te})$; 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 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 t has a weak effect on 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, $M\phi$ and τ in the other hand, are pretty 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

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

at least outside ITB.

II. APPROXIMATION OF THE ELECTRON HEAT DIFFUSIVITY FUNCTION

Let us assume the existence of a non-linear multivariate function, which gives the transport level in tokamak plasma, supposed here purely diffusive. The above correlation analysis suggests an electron heat diffusivity of the form (1) whose the 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 a pure linear transfer function. The training was performed by a Levenberg-Marquardt algorithm [6] with $(A_{Te}, A_{ne}, s, q, \tau)$ as input and $\log(\chi_e/\chi_{gyroBohm})$ as output, only outside ITB in a first time. Among the 13817 data, 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 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, the graph exhibits a smooth so-called critical temperature gradient $(R/L_{Te})c \approx 7\text{-}8$; the 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. A strong reduction of the transport is observed in

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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 sª1.4. 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.

III. 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 trained enough to 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 learnt 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.

DISCUSSION

Facing the burning 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 [9].

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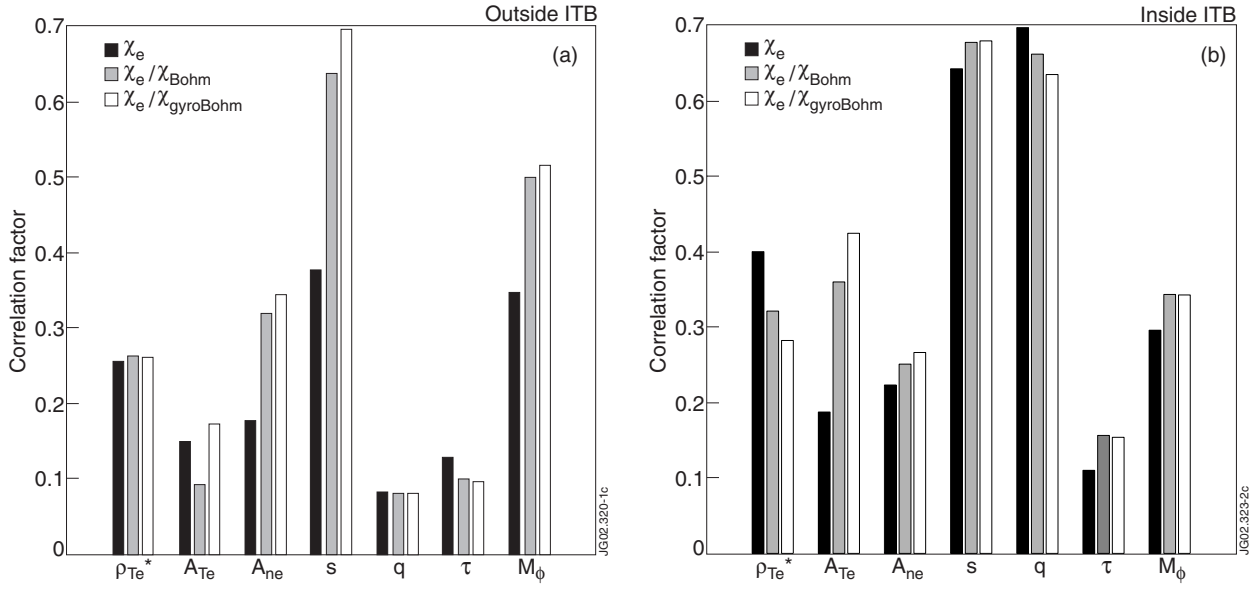[9].   G.T. Hoang et al, this conference.

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. $0 \leq \rho_{Te}^* \leq 0.02$, $0 \leq A_{Te} \leq 15$, $0 \leq A_{ne} \leq 8$, $-1 \leq s \leq 1.5$, $1.2 \leq q \leq 3.8$, $0.3 \leq \tau \leq 1.8$, $0.05 \leq M_\phi \leq 0.6$.
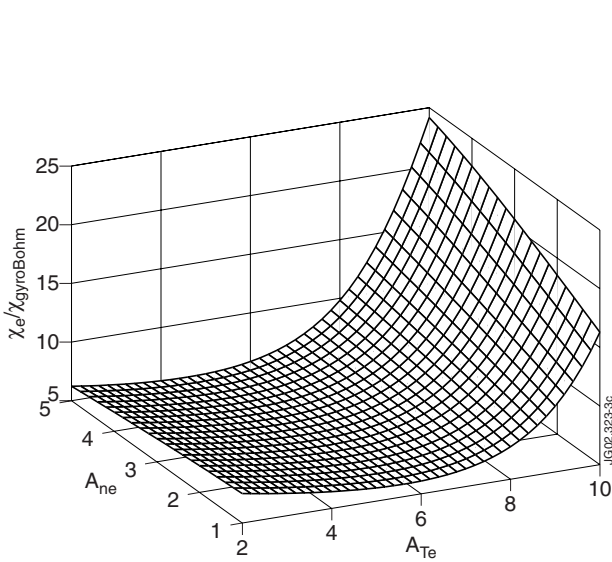

Figure 2: $\chi_e/\chi_{gyroBohm}$ as a function of A_{Te} and A_{ne} after the neural network. $s=-0.5$, $q=2$, $\tau=1$.
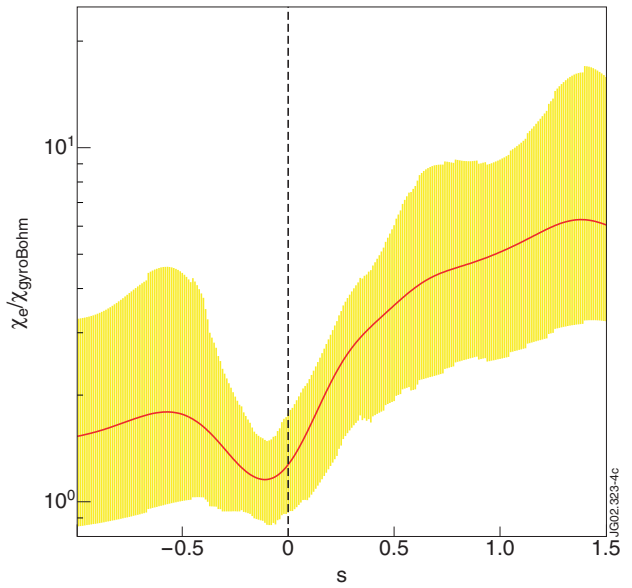

Figure 3: $\chi_e/\chi_{gyroBohm}$ verses the magnetic shear after the neural network. The shaded area stands for the $1-\sigma$ uncertainty of the approximation. $A_{Te}=5$, $A_{ne}=3$, $q=2$, $\tau=1$.
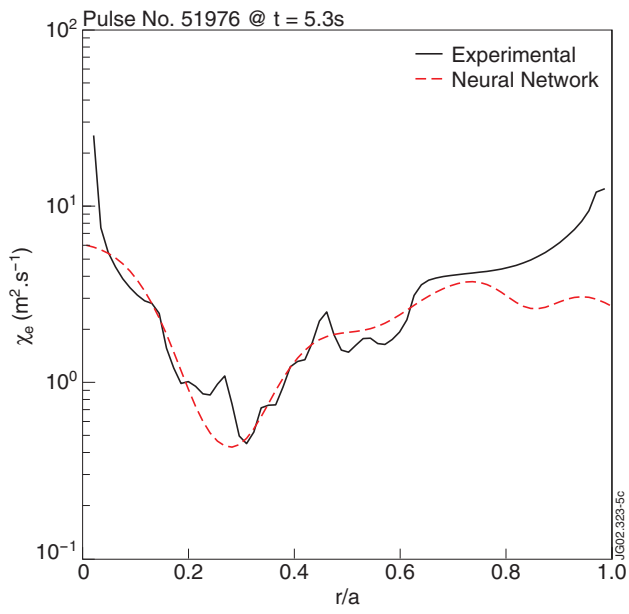
Figure 4: Comparison of experimental and predicted - by neural network - electron heat diffusivities for a JET pulse (Pulse No: 51976) at a time when an ITB is formed.