

PAPER

Machine learning for electrostatic plasma turbulence classification in tokamaks

To cite this article: Hongjian ZHAO *et al* 2025 *Plasma Sci. Technol.* **27** 075105

View the [article online](#) for updates and enhancements.

You may also like

- [Hydrogen isotope effect on the Dimits shift](#)
S.-I. Itoh and K. Itoh
- [Transport characteristics of trapped-electron-mode turbulence nonlinearly interacting with tearing modes in tokamak plasmas](#)
Yifan YAN, , Jiquan LI et al.
- [Simulation of transport in the FT-2 tokamak up to the electron scale with GENE](#)
Salomon Janhunen, Gabriele Merlo, Alexey Gurchenko et al.

Machine learning for electrostatic plasma turbulence classification in tokamaks

Hongjian ZHAO (赵泓鉴)¹, Zehua GUO (郭泽华)², Xiangyu WU (伍湘玉)¹
and Yong XIAO (肖湧)^{1,*}

¹ Department of Physics, Zhejiang University, Hangzhou 310027, People's Republic of China

² Meta Platforms Inc., Menlo Park CA 94025, United States of America

*E-mail of corresponding author: yxiao@zju.edu.cn

Received 10 December 2024, revised 23 April 2025

Accepted for publication 25 April 2025

Published 18 June 2025



CrossMark

Abstract

Artificial intelligence driven by large data is becoming increasingly important in magnetic fusion research. Here, we scan the plasma gradient space for cyclone base case parameters using nonlinear gyrokinetic simulations to generate data for typical electrostatic drift wave turbulences. The main candidates, ion temperature gradient mode (ITG) and trapped electron mode (TEM) are then classified and labeled by conventional methods for the data sets in the linear stage. We then apply a classical machine learning algorithm, namely the support vector machine (SVM), and use plasma gradients or turbulent transport coefficients as the input to classify the type of drift wave turbulence. Simple distance formulae are derived for rapid classification of the turbulence type, demonstrating effectiveness suitable for future theoretical analyses and real-time experimental applications.

Keywords: turbulence, support vector machine, ion temperature gradient mode, trapped electron mode

(Some figures may appear in colour only in the online journal)

1. Introduction

Turbulence exists in nature and the laboratory with multiple temporal and spatial scales. In magnetic fusion plasmas, energy and particle transports caused by electromagnetic fluctuations or turbulence are much larger than those caused by collisional processes [1]. The confining capability of a magnetic fusion device is critically determined by the turbulent transport largely caused by drift wave instabilities [2–4], which are usually excited by free energy stored in the radial temperature or density gradients of the fusion plasmas. Different temperature and density gradients correspond to a variety of drift wave instabilities, typically including the ion temperature gradient mode (ITG) [5], trapped electron mode (TEM) [6], electron temperature gradient mode (ETG) [7], etc. The instabilities excite electromagnetic waves that turn

into turbulence and induce thermal and particle transports. The ITG instability is the dominant mechanism for ion turbulent transport, which can be strongly affected by flow shear and magnetic shear [8]. Due to the special magnetic geometry of tokamaks, trapped electrons can resonate with low-frequency waves to excite another important instability called TEM, which can account for most of the electron transport in tokamaks. ITG and TEM could be suppressed by carefully controlling the ion and electron temperature profiles [9]. Identifying the types of instabilities that drive turbulence is crucial in fusion experiments [10] since it provides essential information for experimentalists to control these instabilities and improve future real-time confinement.

Artificial intelligence (AI), such as machine learning, has recently been pursued to predict the occurrences of tokamak disruption [11] and proactively control the plasma profile evolution. For example, numerous surrogate transport models have been built to predict turbulent transport [12, 13], or ignition threshold [14] based on machine learning. In this

* Author to whom any correspondence should be addressed.

study, we try to use machine learning, specifically the support vector machine (SVM) method [15, 16], to help classify different types of turbulence. This method has been used for effectively classifying experimental data in the low- or high-confinement mode of tokamaks [17], with a hyperplane generated for segmentation after the experimental data are properly transformed in the parameter space. The turbulence data for classification are obtained by first-principles gyrokinetic simulations using the Gyrokinetic Toroidal Code (GTC), which is widely used in the fusion community for simulating plasma turbulence in fusion devices such as tokamaks and stellarators [18, 19]. The GTC code has successfully demonstrated capabilities in simulating ITG, TEM, ETG, kink mode and other important plasma instabilities, as well as producing reliable turbulence data for machine learning analysis [20]. The code has been extensively validated against experiments [21–23]. Using a large amount of instability and turbulence data from GTC, we discovered a hyperplane in the parameter space that can effectively classify the turbulence type. In addition, simple distance formulae are found to rapidly classify turbulence based on simple information of plasma gradients or turbulent transport coefficients, which can be used for future theoretical analysis and real-time experiments.

SVM is a powerful and versatile supervised learning algorithm used for classification and regression tasks. It was introduced by Vapnik [16] and has become a cornerstone in the field of machine learning due to its effectiveness in high-dimensional spaces and its ability to handle non-linear relationships using kernel functions. The main concept of SVM is to find the hyperplane that maximally separates the data points of different classes with the widest margin. This hyperplane is determined by the support vectors, which are the data points closest to the hyperplane and have the greatest influence on its position and orientation. SVMs can be extended to non-linear classification by using kernel functions, such as the linear, radial basis function (RBF), polynomial and sigmoid, which map the original input space into a higher-dimensional space where a linear separation becomes possible.

In this paper, we first introduce the working framework in section 2. Then, the details of dataset generation are given in section 3, including linear instability data and nonlinear turbulence data. In section 4, the feature selection for the turbulence data is carried out. Next, the SVM classification of turbulence is presented in section 5, using either instability drive or featured turbulent quantities as the classifiers. Finally, we conclude this study with some discussion and a brief summary.

2. Working framework

In this study, we utilize the GTC [24] to generate extensive data sets for machine learning applications. GTC is a 3D global gyrokinetic particle simulation code, where the electrons are simulated by a fluid-kinetic hybrid model and the ions are simulated by a gyrokinetic model [25]. Using the small-

ness of electron-ion mass ratio m_e/m_i , the electron response can be treated by a perturbative expansion. The zero order of the expansion reproduces an adiabatic response for the electrons, and the higher-order expansion accounts for wave-particle resonance from parallel and perpendicular motions.

When generating the requisite data sets for machine learning, each GTC simulation can consume a significant amount of computing time. For example, it takes about 6.5 h to run on the Tianhe-3F supercomputer with 1024 nodes for simulating 500 time steps for a typical TEM case. Therefore, it is rather expensive to generate numerous sample data sets. Since no collisions are included in the simulation, the TEM mode in the works refers to the collisionless trapped electron mode or CTEM in the literature [26]. Turbulence itself is a statistical concept and the turbulence quantities exhibit significant fluctuations for both simulation and experimental data, making it challenging to determine the characteristic value for each case. Consequently, it is generally not straightforward to train a large amount of data from the saturated turbulence and nonlinearly fit these turbulence quantities using common AI tools such as machine learning or deep learning. If we treat each simulation case as a single data point, it would be too costly to build a reliable surrogate model that contains a characteristic value for the turbulence. In addition, we tried the Recurrent Neural Network method, which is suitable for sequence analysis, but it requires plenty of data for training and cannot provide better results than the SVM method. In this study, we focus on a relatively limited goal, i.e. to classify different types of turbulence by their nonlinear properties rather than their linear properties. Meanwhile, we find that in order to identify the type of instability with a certain number of parameters using the conventional method, numerous linear simulations are required to find the dispersion relation for determining the instability type by comparing results with the linear theory. Figure 1 shows the dispersion relation from the linear simulation for ITG and CTEM, respectively. Each data point for the linear frequency or growth rate is computed from the linear simulation, which is approximately equivalent to several nonlinear simulations in terms of computing time due to the time-consuming numerical filtering procedure in the global particle simulation.

On the other hand, we note that the SVM method from machine learning has the advantage of using fewer training data sets to achieve better classification accuracy. Therefore, we try a different approach and use the SVM method on the turbulent quantities from a single nonlinear gyrokinetic simulation to classify the type of instability. Moreover, this approach can be used directly in experiments to rapidly determine the turbulence type in real time without resorting to the plasma equilibrium reconstruction and conventional time-consuming linear gyrokinetic simulations.

3. Dataset generation and selection

3.1. Generation of the data set

The prevailing drift wave turbulence in tokamaks is simu-

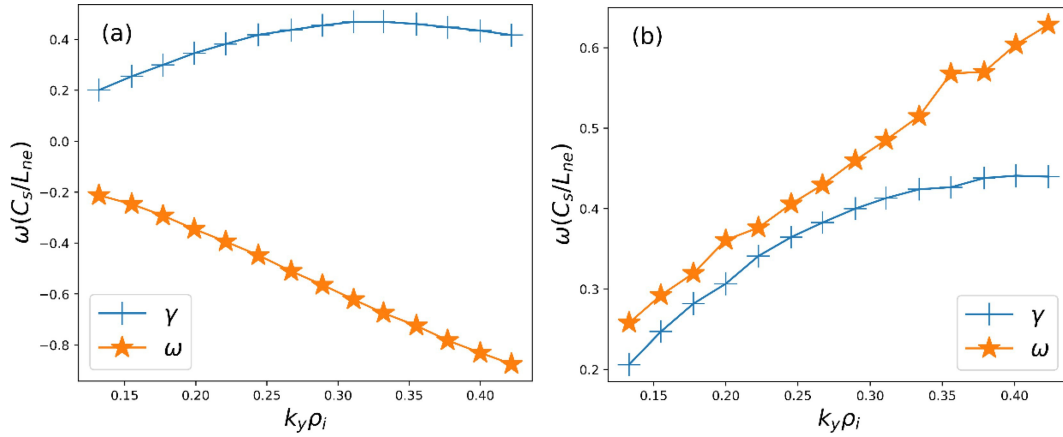


Figure 1. Linear dispersion relation calculated by GTC with parameters: (a) $R/L_{Ti} = 6.92$, $R/L_{Te} = 6.92$ and $R/L_n = 2.22$ for ITG and (b) $R/L_{Ti} = 2.22$, $R/L_{Te} = 6.92$ and $R/L_n = 2.22$ for TEM.

lated by the GTC code in the collisionless electrostatic limit with the following cyclone base case parameters [27]: the density $n_0 = 0.79 \times 10^{20} \text{ m}^{-3}$, the temperature $T_e = T_i = 2.22 \text{ keV}$, $m_i/m_e = 1837$, safety factor $q = 1.4$ and magnetic shear $s = rdq/qdr = 0.78$ on the reference magnetic surface at $r = a/2$. In the simulation, we change the values for the normalized density gradient $R/L_n = R_0 dn/dr$, normalized electron temperature gradient $R/L_{Te} = R_0 dT_e/T_e dr$ and normalized ion temperature $R/L_{Ti} = R_0 dT_i/T_i dr$ in the typical 3D parameter space with a scanning of $6 \times 6 \times 6$ matrix. The corresponding gradient values for each gradient dimension are shown in table 1.

Among the simulation cases, 13 sets of cases were excluded from the data set because no instability was observed since their gradients and gradient ratio $\eta_s = L_{Ts}/L_n$ were below the instability thresholds [28, 29]. We use a total set of 203 plasma gradient combinations to carry out non-linear GTC simulations and a large amount of data was produced from the simulated turbulence. We then proceed to classify various electrostatic drift wave instabilities from the turbulence data. First, we find that the dominant frequencies are way below the electron transit frequency, i.e. $\omega/(k_{\parallel} \sqrt{T_e/m_i}) \sim 0.02 \ll 1$. Thus, the contribution of the passing electrons is dominantly adiabatic and we shall focus on the kinetic response of the trapped electrons. This result is further verified by comparing the linear growth rates with and without the passing electrons, as shown in figure 2. It can be seen that for all cases the relative difference between the growth rates is less than 16%. Therefore, with the selected parameters, the passing electrons respond adiabatically and contribute little to the instability. Thus, when the electrons are the proactive species that drive the instability, the instability can only be considered as the TEM mode, with the ETG mode excluded from the candidate instabilities.

In general, ITG and TEM can co-exist as two branches of the drift wave instability. It is relatively easier to distinguish these two instabilities in the parameter regions where only one branch of modes is excited and the other branch of modes is purely damping [30]. For example, in case #161 where $\eta_i = L_n/L_{Ti} = 1.0$ and $\eta_e = L_n/L_{Te} = 4.4$, the ITG

Table 1. Normalized plasma profile gradients used in the turbulence simulation, where $\alpha = (n, T_i, T_e)$

#	R/L_{α}
1	2.5
2	4.2
3	5.93
4	7.67
5	9.39
6	10.9

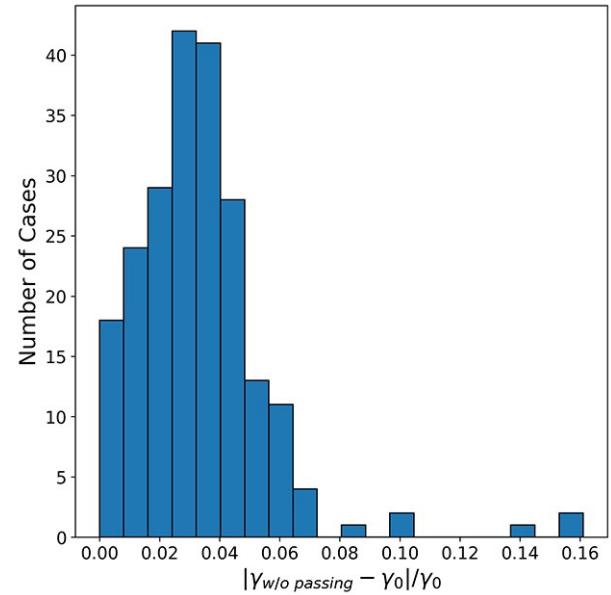


Figure 2. Difference in the growth rate between the case with only trapped electrons and the case with both trapped electrons and passing electrons, where $\gamma_{w/o \text{ passing}}$ refers to the growth rate from the cases without passing electrons.

branch cannot be excited and this case can only be considered as TEM-dominant; in case #116 where $\eta_i = 4.0$ and $\eta_e = 1.0$, the instability is ITG-dominant. Therefore, with minimal effort, we can determine the type of instability in these parameter regions.

However, for the other cases, it is difficult to distinguish

between ion mode and electron mode since both can be unstable. The GTC code uses the δf algorithm to calculate linear instability and simulate nonlinear turbulence in the sense of perturbation theory [31]. With this δf algorithm, the entropy of the particle species α in the simulation is represented by $\iint d^3x d^3v \delta f_\alpha^2$. When the instability increases, the entropy will keep increasing with time. By comparing the initial growth of the entropy for ions and electrons, we can determine which particle species dominates the instability. This unique feature can be used to determine whether the type of instability is driven by ions or electrons, i.e. ITG or TEM.

At the fully developed turbulent stage in each simulation case, we carry out a time average for the selected data sequence to obtain one data point. In this way, a total of 1411 data points are generated by varying the density and temperature gradients shown in table 1 and comparing the initial growth of the electron and ion entropy, among which 826 data points were identified as TEM and the remaining 585 data points as ITG, with a ratio of approximately 3:2.

3.2. Feature selection

Next, we need to determine what physical quantities should be selected as the input features for the SVM classification algorithm. First, we calculate the correlations between some physically important candidate features: electric potential amplitude ϕ^{rms} , zonal flow potential ϕ_{00}^{rms} , ion particle diffusivity D_i , ion heat conductivity χ_i and the corresponding electron transport quantities D_e and χ_e . The correlation coefficient $\text{Corr}(\alpha, \beta)$ for arbitrary physical quantities α and β is calculated using the following formula:

$$\text{Corr}(\alpha, \beta) = \frac{\sum_i \alpha_i \beta_i}{\sqrt{\sum_i \alpha_i^2 \sum_i \beta_i^2}}. \quad (1)$$

The resultant correlation coefficients between different physical quantities are shown in table 2. We note that $\text{Corr}(\phi^{\text{rms}}, \phi_{00}^{\text{rms}}) = 0.89$ and $\text{Corr}(D_i, D_e) = 1.00$, which shows that the physical quantities in these pairs are interchangeable. This makes physics sense since the zonal flows are self-consistently generated by the turbulence, and the radial ambipolarity [1, 32] is well preserved for turbulent particle flux, as it should be. Thus, we can remove ϕ_{00}^{rms} and D_e from the feature list to ensure the independence of each feature quantity. The rest of the feature quantities have no strong correlations or dependences between them and can be considered to be independent variables.

Finally, we employ the linear SVM method with L1 regularization [33] to conduct the feature selection in the machine learning process. This method can reduce the model complexity and thus avoid overfitting. With the penalty coefficient $C = 0.0125$, ϕ^{rms} is filtered out of the model. What is more, it is difficult for experimental diagnostics to obtain the electric potential fluctuations in the core plasmas due to its extreme high temperature. Thus, even from the experimental point of view, it is unfavourable to include ϕ^{rms} in the physics modelling. Next, we add parameters term by term

Table 2. The correlation coefficients between the selected alternative features.

	ϕ^{rms}	ϕ_{00}^{rms}	D_i	χ_i	D_e	χ_e
ϕ^{rms}	1.00	0.89	0.47	0.38	0.46	0.37
ϕ_{00}^{rms}	0.89	1.00	0.40	0.28	0.40	0.28
D_i	0.47	0.40	1.00	-0.25	1.00	0.33
χ_i	0.38	0.28	-0.25	1.00	-0.25	0.10
D_e	0.46	0.40	1.00	-0.25	1.00	0.33
χ_e	0.37	0.28	0.33	0.10	0.33	1.00

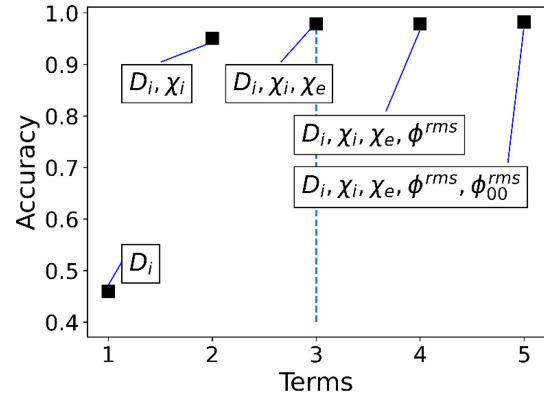


Figure 3. Accuracy of linear SVM classification on the validation set versus the complexity of the physics models.

and employ 5-fold cross-validation [15] to find out whether the model with the aforementioned three physical quantities is accurate enough for the turbulence classification, as shown in figure 3. We note that including extra physical quantities would not introduce more accuracy to the classification. Based on these arguments, we finally choose three transport coefficients, D_i , χ_i and χ_e , as the input features to classify the turbulence type. We normalize these features by the gyroBohm diffusivity $D_{\text{GB}} \equiv \rho_i e B_0 / a T_e$, where $\rho_i = \sqrt{m_i T_i} / (e B_0)$ is the ion gyroradius, $a = 0.36 R_0$ with a the tokamak minor radius, R_0 the tokamak major radius and B_0 the magnetic field at the magnetic axis.

4. SVM classification results

In this section, we use SVM to classify the data set from two perspectives. First, we classify the instability type using the simulation parameters or the instability drives as the input quantities, which is similar to some previous references [12, 34], and then we use the selected feature quantities from the turbulent stage as the input quantities for classification. In this way, we can classify the instability type by the turbulence quantities, which caters more to experimental needs.

4.1. Parameter classification

We use the Python library of Scikit-Learn to implement the SVM algorithm and perform the classification with the simulation input parameters first, i.e. the instability drives or the plasma temperature and density gradients. The normalized

characteristic gradients ($R/L_n, R/L_{Ti}, R/L_{Te}$) are regarded as the input features and the type of instability is classified according to the aforementioned entropy-based criterion, as shown in figure 4, where the blue dots represent TEM-dominant cases and the red dots represent the ITG-dominant cases. The dividing plane is found by the linear SVM classification, with an accuracy as high as 98%. The confusion matrix is shown in table 3, which demonstrates that the SVM classification can correctly determine the type of instability by using the plasma gradient combination. In addition, we can also obtain an analytic formula for the dividing plane with three alternative free parameters, R/L_n , η_e and η_i :

$$\tilde{d} = 1 - \frac{2.1}{R/L_n} + 0.63\eta_e - 1.0\eta_i. \quad (2)$$

It is found that the TEM mode dominates for $\tilde{d} > 0$ and the ITG mode dominates for $\tilde{d} < 0$. The conclusion is consistent with the existing theory in a toroidal system; the ITG mode is driven by η_i , while larger values of R/L_n and η_e tend to excite the TEM mode [35]. This analytic distance formula can help us to rapidly determine the kind of instability for a given set of instability-driven plasma gradients, and to locate the appropriate parameter region for exploring the ITG-TEM transition physics, which can find wide application in both theoretical and experimental analyses.

4.2. Turbulence classification

In many cases, the feature physical quantities during the

Table 3. The confusion matrix of classification for simulation cases by linear SVM.

		Prediction	
Reference	ITG	64	2
	TEM	4	139

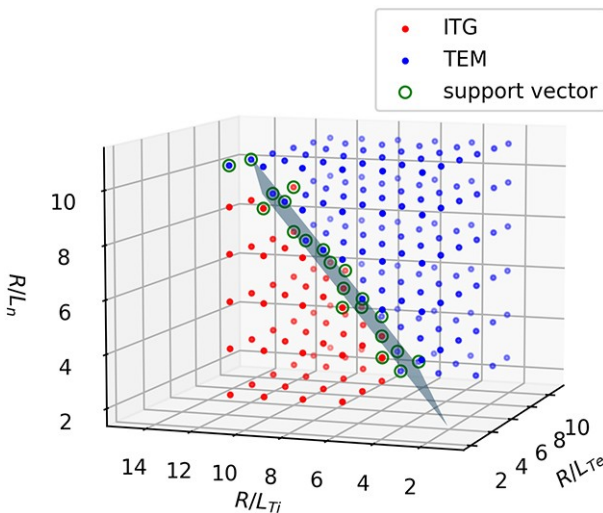


Figure 4. Turbulence classification for the simulation cases with varying gradient drives ($R/L_n, R/L_{Ti}, R/L_{Te}$) in the parameter space, with the dividing plane generated by the SVM algorithm.

turbulent stage can be measured by advanced diagnostics [36, 37]. We can directly use these turbulent quantities to classify the type of instability. First, we run numerous GTC nonlinear gyrokinetic simulations by varying the plasma gradients shown in table 1 and select the desired feature turbulence quantities as the training and test data sets using the procedure shown in section 3. In this way, we collected a total number of 1411 data points for each feature quantity from these nonlinear gyrokinetic simulations. These data are then randomly split into a training data set and a testing data set with a ratio of 8:2, leading to a total of 283 testing data points. Then, we use the grid search algorithm [38] to determine the proper parameters for the classifier.

At first, the linear kernel is used for the data training. It is found that when the penalty coefficient $C = 13.5$, the SVM algorithm on the test data set yields an accuracy of 97.17% and on the training data set an accuracy of 97.52%. We then obtain the following distance formula using the linear kernel in the Scikit-Learn library:

$$d = 7.64D_i - 6.06\chi_i + 4.05\chi_e + 0.35, \quad (3)$$

where d represents the distance to the dividing hyper-plane.

For the training cases, when $d > 0$, it is found to be the TEM-dominant case, and when $d < 0$, it is found to be the ITG-dominant case, as shown in figure 5(a). Moreover, a large positive d value suggests turbulence deep in the TEM region, and a large negative value of d suggests turbulence deep in the ITG region. We can even make further deductions about the turbulent properties through the distance formula in equation (3). For example, in the typical ITG turbulence, the electron particle diffusivity D_e and thermal conductivity χ_e ought to be both much smaller than the ion thermal conductivity χ_i since the ions are proactively resonant with the unstable waves [39]. Thus, in order to obtain $d < 0$ for the ITG turbulence in our notation, the sign before χ_i should be negative. However, in the TEM turbulence, the positive sign before D_i suggests that the TEM turbulence produces more particle transport than the ITG turbulence does. In order to obtain $d < 0$ for the ITG turbulence, the contribution from the particle diffusivity ought to be minimal in the ITG turbulence. We also note that the three coefficients before D_e , χ_e and χ_i are close to each other, which suggests that the ITG turbulence ought to produce more ion heat transport than the electron heat transport to keep $d < 0$.

Finally, we switch to the radial basis function (RBF) kernel to carry out the turbulence classification. With $C = 30$ and $\gamma = 0.1$, we obtain an accuracy of 98.23% for the classification. The classification report on the test set is shown in table 4, which demonstrates that the classification method developed here has a considerable degree of accuracy, and the confusion matrix shown in table 5 shows that most of data points were classified correctly. The distribution of the data points and the dividing surface are shown in figure 5(b). In the test set of 283 cases, all ITG data points and almost all TEM data points are correctly classified, and only five TEM data points are incorrectly classified as ITG. All five incorrectly classified data points are located in the parameter

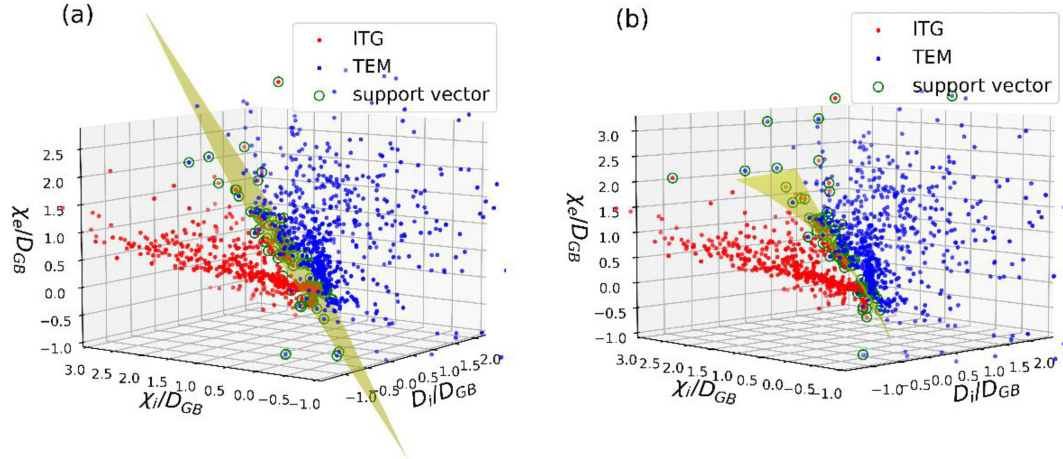


Figure 5. Data distribution of the training set is shown in the (D_i, χ_i, χ_e) space with the dividing plane from (a) linear classification for the training set and (b) RBF-kernel classification for both the training and test sets.

Table 4. The turbulence classification accuracy report for SVM with RBF kernel.

	Precision	Recall	F1-score
ITG dominant	95.90%	100.00%	97.91%
TEM dominant	100.00%	96.99%	98.47%
Accuracy			98.23%

Table 5. The confusion matrix of classification for SVM with RBF kernel.

		Prediction	
Reference	ITG	117	0
	TEM	5	161

space of the ITG-TEM transition region, which may be the cause of the classification difficulties. The nonlinear classification only gives slightly more accurate results than the linear classification. It can be seen from the shape of the dividing surface that the linear classification approximation is accurate enough in most regions.

5. Discussion and conclusion

In experiments, transport coefficients can be obtained using numerical transport codes such as TRANSP [40]. Various diagnostic methods can directly measure plasma profiles, such as electron density (n_e), electron temperature (T_e), ion temperature (T_i), radiated power (P_{rad}) and current profile (j). These measurements allow transport codes to calculate particle diffusivities (D_i , D_e) and heat conductivities (χ_i , χ_e) at specific locations, often close to real time. Typically, gyrokinetic simulations are required to identify the dominant instability, which can take up to about several hours. However, by applying our classification model, experimentalists can input diffusivities calculated from TRANSP and immediately determine the type of instability, which could signifi-

cantly benefit the experimental operation. For instance, if one aims to reduce ion energy loss and increase the ion temperature in the tokamak core plasma, it is effective to flatten the ion temperature profile adjusting auxiliary ion heating if the instability is identified as the ITG mode. On the other hand, if the instability is identified as TEM, one can suppress turbulent transport more effectively via adjusting electron heating strategy to flatten the electron temperature profile. By identifying the instability type in real time, experimentalists can streamline and optimize their operational strategies.

There are still some unresolved issues regarding our discoveries. For instance, the ITG-TEM interface in the parameter space is found to be a flat plane, as shown in figure 4, instead of a curved surface in the parameter space. We further note that in the gyrokinetic simulation, physical quantities often exhibit a high fluctuation level in the turbulent phase, which could lead to a high computing cost in building a surrogate model for the turbulent transport, i.e. using nonlinear regression methods, such as the neural network, may not even be computationally feasible. Future work will also explore extending the parameter space to cover more important physics parameters, such as magnetic shear, collisionality and impurity content. Furthermore, multi-type classification can be readily achieved [15], if some extra instability types are observed in simulations. The number of simulations will increase rapidly and soon become formidable when the scanning parameter space is expanded. The reinforcement learning technique may be used to narrow down the parameter space. For all the preceding efforts, a close collaboration with experimentalists will be indispensable.

In this study, the machine learning technique based on SVM, with proven effectiveness, has been used to classify the nature of turbulence. We use the gyrokinetic code GTC to carry out numerous linear and nonlinear simulations with cyclone base case parameters, and classify the instability type as either ITG or TEM for each linear simulation by inspecting the role of the trapped electrons in the simulations and comparing the entropy growth rates between ions

and electrons. With time history of the target physical quantities, the SVM method is employed to achieve automatic data selection. The SVM method has also been employed to find an analytic distance formula for instability classifier with the input as the plasma gradients. This simple distance formula is very useful for classifying instability and turbulence in a quick and accurate way, which can find wide application in real-time experiments and theoretical analysis. We carry out a feature selection via correlation analysis and identify the turbulence quantities including χ_i , χ_e and D_e as the feature quantities. These feature turbulence quantities have been used to find a second SVM classifier, i.e. a second distance formula in equation (3), which can accurately classify the electrostatic drift wave instability types with accuracies up to 97.52% and 98.23% with the linear and RBF kernel, respectively. Moreover, the obtained distance formulae in equations (2) and (3) can also be used to measure the depth of the turbulence in the classified region, which is consistent with the current physics understanding of electrostatic drift wave turbulence. In other words, for some given feature turbulence quantities, which could come from the experimental diagnostics, we can determine from the distance formula in equation (3) whether the turbulence is in the deep ITG region, the deep TEM region or the ITG-TEM transition region. These quantitative results may assist experimentalists to regulate fusion plasma turbulence in real time.

Acknowledgments

The authors are grateful to Prof. Zhihong Lin and Drs. Jian Bao, Pengjun Sun and Ge Dong for fruitful discussions. This study was supported by National MCF Energy R&D Program of China (No. 2019YFE03060000) and by National Natural Science Foundation of China (No. 12275013).

References

- [1] Chen F F 2016 *Introduction to Plasma Physics and Controlled Fusion* 3rd ed (Cham: Springer)
- [2] Singh R and Diamond P H 2020 *Phys. Plasmas* **27** 042308
- [3] Coppi B, Rosenbluth M N and Sagdeev R Z 1967 *Phys. Fluids* **10** 582
- [4] McDevitt C J, Tang X Z and Guo Z H 2017 *Phys. Plasmas* **24** 082307
- [5] Freidberg J P and Wesson J A 1970 *Phys. Fluids* **13** 1009
- [6] Cheng C Z and Chen L 1981 *Nucl. Fusion* **21** 403
- [7] Lee Y C et al 1987 *Phys. Fluids* **30** 1331
- [8] Li J C, Dong J Q and Liu S F 2020 *Plasma Sci. Technol.* **22** 055101
- [9] Ernst D R et al 2009 *Phys. Plasmas* **16** 055906
- [10] Kotschenreuther M et al 2019 *Nucl. Fusion* **59** 096001
- [11] Kates-Harbeck J, Svyatkovskiy A and Tang W 2019 *Nature* **568** 526
- [12] Li H et al 2021 *Plasma Sci. Technol.* **23** 115102
- [13] Ma C H et al 2020 *Phys. Plasmas* **27** 042502
- [14] Yang C et al 2022 *Phys. Plasmas* **29** 082702
- [15] Bishop C M 2006 *Pattern Recognition and Machine Learning* (New York: Springer)
- [16] Vapnik V N 1995 *The Nature of Statistical Learning Theory* (New York: Springer)
- [17] Vega J et al 2009 *Nucl. Fusion* **49** 085023
- [18] Lin Z et al 1998 *Science* **281** 1835
- [19] Wang H Y et al 2020 *Phys. Plasmas* **27** 082305
- [20] Dong G et al 2021 *Nucl. Fusion* **61** 126061
- [21] Wei X S et al 2025 *Nucl. Fusion* **65** 026026
- [22] Yang H W, Zhou T C and Xiao Y 2021 *Nucl. Fusion* **61** 056006
- [23] Brochard G et al 2024 *Phys. Rev. Lett.* **132** 075101
- [24] Lin Z et al 2000 *Phys. Plasmas* **7** 1857
- [25] Lin Z H and Chen L 2001 *Phys. Plasmas* **8** 1447
- [26] Adam J C, Tang W M and Rutherford P H 1976 *Phys. Fluids* **19** 561
- [27] Dimits A M et al 2000 *Phys. Plasmas* **7** 969
- [28] Dong J Q, Horton W and Kim J Y 1992 *Phys. Fluids B: Plasma Phys.* **4** 1867
- [29] Coppi B and Rewoldt G 1974 *Phys. Rev. Lett.* **33** 1329
- [30] Rewoldt G, Lin Z and Idomura Y 2007 *Comput. Phys. Commun.* **177** 775
- [31] Parker S E and Lee W W 1993 *Phys. Fluids B: Plasma Phys.* **5** 77
- [32] Allis W P and Rose D J 1954 *Phys. Rev.* **93** 84
- [33] Ng A Y 2004 Feature selection, L_1 vs. L_2 regularization, and rotational invariance In: *Twenty-First International Conference on Machine Learning Banff*: ACM 2004: 78
- [34] Citrin J et al 2015 *Nucl. Fusion* **55** 092001
- [35] Ernst D R et al 2004 *Phys. Plasmas* **11** 2637
- [36] Ryter F et al 2001 *Plasma Phys. Control. Fusion* **43** A323
- [37] Schneider B S et al 2019 *Plasma Phys. Control. Fusion* **61** 054004
- [38] Lerman P M 1980 *Appl. Statist.* **29** 77
- [39] Rewoldt G and Tang W M 1990 *Phys. Fluids B: Plasma Phys.* **2** 318