



**INVESTIGATING THE DEPENDENCE ON MACHINE SIZE OF THE
ENERGY CONFINEMENT IN TOKAMAKS USING
DATA-DRIVEN METHODS**

Master Thesis
presented by

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June 15, 2023



European Master of Science in
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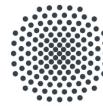
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Universität Stuttgart



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ABSTRACT

Accurately determining the energy confinement time of a fusion device is essential in the decision-making process for constructing such machines. Various methods have been employed to study this parameter, including simulation codes and empirical scaling laws. The latter, being the preferred option, led to the design of the International Thermonuclear Experimental Reactor (ITER) in 1998, aided by the global H-mode confinement database. The major radius of a tokamak directly impacts both the confinement time and the cost of the machine. In the design of ITER, it was found that the confinement time scaled with the major radius by a factor of two. However, with the recent update of the database and a reevaluation of the analysis, it results that there is a weaker dependence on this parameter.

The primary objective of this thesis is to contribute to understanding the factors behind the reduced significance of machine size in energy confinement. The project is divided into three key parts. Firstly, the focus is on identifying the key observations within the new dataset that have the most influence on this parameter. Statistical tests are then applied to examine whether any data-related issues, such as collinearity, are contributing to the observed effects. The second part employs two different machine-learning algorithms, namely Gaussian process and random forests, to identify the variables that characterize the decrease in the influence of the major radius. These variables may not necessarily belong to the scaling law of the energy confinement time. In the final part, the insights gained from the preceding chapters are related to tokamak physics. This includes revisiting the theory of instabilities and exploring engineering aspects that characterize each tokamak in the dataset.

The results indicate that the decrease in influence on machine size is not solely attributed to data-related issues. Instead, four main parameters emerge as predictors of whether an observation will be affected by this decrease. These parameters include the normalized ion gyroradius, the normalized ion collision frequency, the safety factor, and the normalized plasma beta. Applying the prediction algorithm to these parameters for new machines, such as ITER, suggests that the shots are more likely to be unaffected by the decrease in influence. Additionally, it is observed that spherical machines exhibit distinct clusters within these four variables, displaying notable differences from less compact machines. However, the dataset only comprises 3.8% of spherical machines, indicating a need for more extensive data on spherical tokamaks to further enhance the project's outcomes.

Understanding the factors contributing to the reduced significance of machine size in energy confinement has major implications for the design and optimization of future fusion devices, leading to more efficient and cost-effective solutions. Furthermore, the need for additional data on spherical tokamaks underscores the importance of expanding research efforts in this area to refine the predictive models for future fusion devices.

Keywords: Global H-mode confinement database, Energy confinement time, Tokamak, Major radius, Gaussian process, Random forest, Data analytics.

NOTATION

ACRONYMS AND CONNOTATIONS

ELMs	Edge Localized Modes (also referred as ELMy)
H-mode	High-confinement mode
IAEA	International Atomic Energy Agency
ITER	International Thermonuclear Experimental Reactor
L-mode	Low-confinement mode
LCFS	Last Closed Flux Surface
MHD	Magnetohydrodynamics
OLS	Ordinary Least Squares
Shot	Single experimental run or discharge of a tokamak device
Subset	Reduction in number of rows, when referring to a dataset
w.r.t.	with respect to

DATABASES

DB2	Global H-confinement mode, version 2.8 (also as DB2.8 or DB2P8)
DB5	Updated DB5, version 5.2.3
STDB5	Standard criteria applied to DB5 and ELMy subset
new_DB5	Subset of STDB5, without DB2 observations
decreasing_DB5	Subset of new_DB5
small_ds	Subset of decreasing_DB5, without DB2 observations
big_ds	Subset of decreasing_DB5, without DB2 observations
clean_DB5	Modified STDB5, with a treatment in missing values and reduction of columns

GENERAL MATHEMATICS

$\mathcal{O}(\cdot)$	Big-O notation, denoting the complexity of an algorithm
∇	Vector differential nabla-operator
\mathbf{I}_n	$n \times n$ identity matrix
T	Transpose
$\mathbb{E}[\cdot]$	Expected value of one input \cdot
$k(\mathbf{x}, \mathbf{x}')$	kernel function of two inputs \mathbf{x}, \mathbf{x}'

$\text{Cov}[\mathbf{x}, \mathbf{x}']$	Covariance of two inputs \mathbf{x}, \mathbf{x}'
$\text{Var}[\cdot]$	Variance of one input \cdot
M	Total number of columns in dataset
n	Number of rows/observations in a dataset
\mathbf{X}	$n \times (M + 1)$ matrix representing a database
x_i	i -th row of \mathbf{X}
\mathbf{y}	Target variable, an n -dimensional column vector
$\hat{\beta}$	Parametric vector, an $(M + 1)$ -dimensional column vector
h_i	Leverage of the i -th observation
r_i	Studentized residual of the i -th observation
ε	Gaussian noise, an n -dimensional column vector
E	Entropy of a dataset
S_{ij}	Similarity between the x_i and x_j observations
$Z \sim \mathcal{N}(0, 1)$	Random Variable Z follows a normal distribution, with mean 0 and a standard deviation 1

TOKAMAK-RELATED AND PHYSICS SYMBOLS

μ_0	Vacuum magnetic permeability	$4\pi \times 10^{-7} \text{ Hm}^{-1}$
q	Elementary charge	$1.602176634 \times 10^{-19} \text{ C}$
\bar{n}_e	Averaged electron density	10^{19} m^{-3}
κ_a	Elongation of the LCFS	m^3
a	Minor radius of the tokamak	m
R_{geo}	Major radius of the tokamak	m
P_{fus}	Fusion power	MW
$P_{l,th}$	Thermal power lost due to the transport through the LCFS	MW
P_α	Energy carried by the alpha particles contributing to D-T fuel	MW
P_Ω	Ohmic heating	MW
P_{aux}	Auxiliary heating power	MW
P_{rad}	radiated power	MW
B_θ	Poloidal magnetic field	T
B_t	Toroidal magnetic field	T
I_p	Plasma current	MA
$\langle \sigma v \rangle$	Highest fusion reaction rate	$\text{m}^3 \text{s}^{-1}$

$\tau_{E,th}$	Energy confinement time	s
\hat{T}	Total averaged temperature of the plasma	eV
ω_c	Ion cyclotron frequency	Hz
M_{eff}	Effective atomic mass of the plasma	amu
β_t	Plasma pressure normalized to B_t ($= 2\mu_0\bar{n}_e\hat{T}/B_t$)	-
ϵ	Inverse aspect ratio ($= a/R_{geo}$)	-
γ_{rad}	Parametrization constant for defining radiative losses $\in [0, 1]$	-
ν_*	Ion collision frequency normalized to bounce frequency of trapped particles.	-
ρ_*	Ion gyroradius normalized to a .	-
Q	Fusion Gain ($= \hat{P}_{fus}/P_{aux}$)	-
q_{95}	Plasma safety factor ($= \epsilon B_t/B_\theta$) at the 95% poloidal flux surface	-
q_{cyl}	q_{95} with cylindrical approximation	-
α_x	Regression coefficient of the x variable in the scaling law for $\tau_{E,th}$	-
χ_x	Regression coefficient of the x variable in the scaling law for $\omega_i \cdot \tau_{E,th}$	-

I

INTRODUCTION

Around 1919, Rutherford conducted numerous experiments at the University of Manchester, which resulted in the first artificial nuclear reaction performed on Earth. Later, scientists started dreaming of utilizing this energy for electricity production. Initially, linear devices of magnetic confinement were studied, but quickly discarded due to their instabilities. Then, toroidal devices were analyzed. It was noted that a strong twisted magnetic field along the torus is crucial for circular confinement to avoid charge accumulation, which terminates confinement in this configuration. The creation of these particular field lines can be achieved in two devices: tokamaks and stellarators. Stellarators make use of external coils, some of which revolve helically around the plasma. In tokamaks, there is an induced net toroidal plasma current [1], [2]; Figure 1.1 shows the difference between these devices.

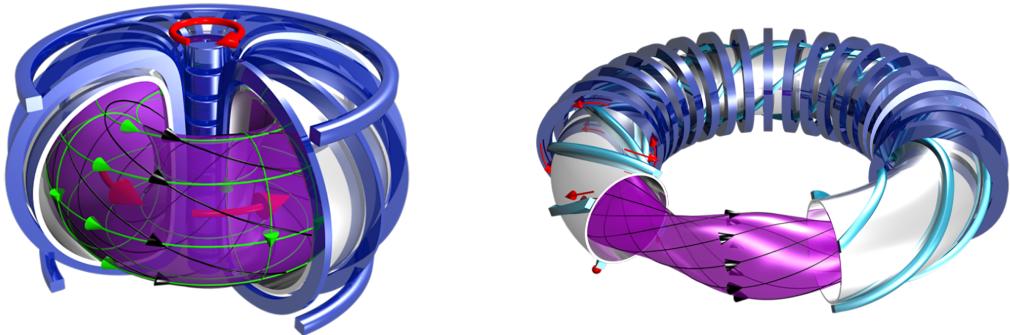


Figure 1.1: In both images, the toroidal coils are shown in dark blue, the red arrows represent a current, and the black arrows represent the required rotational transform of the magnetic field lines. LEFT: tokamak showing the poloidal magnetic field lines, as green arrows, resulting from the presence of the induced current. RIGHT: stellarator having helical coils, in light blue [2]. Images from [3].

Nowadays, tokamaks are the popular option for fusion research due to their simple geometry. The International Thermonuclear Experimental Reactor (ITER) is a megaproject composed of 35 nations dedicated to investigating tokamak physics and helping to be one step closer to employing fusion energy for peaceful usage [4].

In 1991, the International Atomic Energy Agency (IAEA) released a document indicating the conceptual design of ITER, where they mentioned two ways of predicting the energy confinement time: by codes modelling the transport in the plasma and by constructing an empirical scaling law, with the latter being the preferred option [5]. Today, this method remains the dominant approach when investigating the energy confinement time of any tokamak, mainly because a direct estimate of this variable is still unavailable, even with the significant advancements in the field of theoretical physics in tokamaks [6], [7].

1.1 Energy Confinement Time

Since the plasma experiences a decrease in turbulent transport and improved confinement is achieved during the high-confinement mode (H-mode) this technique is expected to be the nominal inductive operation for ITER; with edge localized modes (ELMs) – small periodic bursts of energy and particles ejected from the plasma that impact the plasma-facing components [8], [9].

The expression of the energy confinement time $\tau_{E,th}$ [s] results from an empirical standard power law conformed by eight plasma parameters: plasma current I_p [MA], toroidal magnetic field B_t [T], central line-averaged electron density \bar{n}_e [$\cdot 10^{19} \text{ m}^{-3}$], thermal power lost due to the transport through the last closed flux surface (LCFS) $P_{l,th}$ [MW], major radius R_{geo} [m], elongation of the LCFS $\kappa_a = V/(2\pi R_{geo}\pi a^2) = b/a$ (with V [m^3] being the plasma volume inside the LCFS, a [m] the minor radius of the tokamak, and $2b$ [m] the height between the upper and lower plasma edge), inverse aspect ratio $\epsilon = a/R_{geo}$, and the effective atomic mass of the plasma M_{eff} [8]; see Figure 1.2 for a visual description of the plasma geometrical parameters. The scaling law of the energy confinement time is:

$$\tau_{E,th} = \alpha_0 \cdot I_p^{\alpha_I} \cdot B_t^{\alpha_B} \cdot \bar{n}_e^{\alpha_n} \cdot P_{l,th}^{\alpha_P} \cdot R_{geo}^{\alpha_R} \cdot \kappa_a^{\alpha_\kappa} \cdot \epsilon^{\alpha_\epsilon} \cdot M_{eff}^{\alpha_M}. \quad (1.1)$$

Each accompanying coefficient α_x is estimated by applying the logarithm to Eq. (1.1) and then using the ordinary least squares (OLS) regression technique. There is another version that considers the triangularity δ , another geometrical parameter that characterizes the plasma cross-section of the LCFS; however, I will not consider this parameter as it turns out to have a weak dependence for the dataset of interest [6].

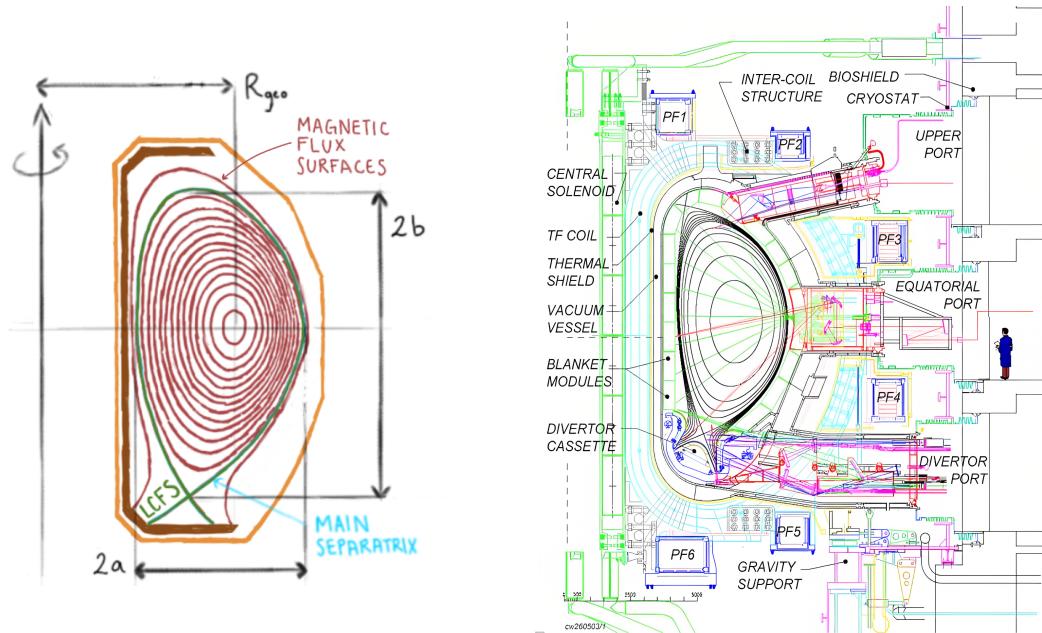


Figure 1.2: LEFT: A drawing of a simple poloidal cross-section of a tokamak is used to depict its geometrical parameters; open field lines ending in an open divertor. More on flux surfaces in Chapter 4. RIGHT: ITER poloidal cross-section is shown to illustrate a more complex plasma configuration. Image from [10]. It is worth noting that there is the possibility of a second separatrix at the top and that the open field lines could end in a closed divertor.

The data used to estimate the regression coefficients has been collected since 1989, by the H-mode Database Working Group. This data is referred to as the Global H-mode Confinement Database and, since 2001, it follows a framework established by the International Tokamak Physics Activity (ITPA).

Version 2.8, ELMMy subset, of this database (DB2.8¹) was utilized to estimate ITER's physics and its design. DB2.8 is characterized by 9 devices: ASDEX, ASDEX-UPGRADE (AUG), Alcator C-MOD, DIII-D, JET, JFT-2M, JT-60U, PBXM, and PDX. It contains 1310 data points [6]. When computing the OLS to Eq. (1.1) using DB2.8, one obtains the following regression parameters

$$\tau_{E,th} = 0.05 \cdot I_p^{0.78} \cdot B_t^{0.32} \cdot \bar{n}_e^{0.43} \cdot P_{l,th}^{-0.67} \cdot R_{geo}^{2.22} \cdot \kappa_a^{0.39} \cdot \epsilon^{0.58} \cdot M_{eff}^{0.18}. \quad (1.2)$$

Nowadays, one can work with the updated version of the global H-mode confinement database DB5 version 2.3, released in 2021. This database is characterized by having 14,153 observations of 19 different devices: ASDEX, AUG, Alcator C-MOD, COMPASS, DIII-D, JET, JFT-2M, JT-60U, MAST, NSTX, PBXM, PDX, START, T-10, TCV, TDEV, TEXTOR, TFTR, TUMAN-3M [11]. When considering the ELMMy subset of DB5 with the standard criteria (STDB5), composed of 6,252 observations and 18 devices (without TUMAN-3M), one obtains that the regression parameters of Eq. (1.1) are the following:

$$\tau_{E,th} = 0.08 \cdot I_p^{1.13} \cdot B_t^{0.07} \cdot \bar{n}_e^{0.17} \cdot P_{l,th}^{-0.68} \cdot R_{geo}^{1.45} \cdot \kappa_a^{0.28} \cdot \epsilon^{0.06} \cdot M_{eff}^{0.21}. \quad (1.3)$$

The standard criterion is the same applied to previous databases and it is characterized by shots having [6]:

- (i) no pellet fueling,
- (ii) no strong internal transport barriers,
- (iii) no excessive magnetohydrodynamics activity near the β_t -limit²,
- (iv) steady energy content,
- (v) limited radiative power,
- (vi) limited fast particle energy content, and
- (vii) minimum safety factor ($q_{95} \geq 2.5$).

Considering this, when comparing Eq. (1.2) with Eq. (1.4) one can notice that, except for $P_{l,th}$, all the regression parameters change notoriously, this is due to the complexity and uncertainty in the database; it is for this reason that the confinement scaling has been studied using the geodesic least squares regressor, a tool that is more robust for this type of dataset compared to OLS [6], [12].

One might think that the greatest influence on R_{geo} may come from the presence of spherical tokamaks (MAST, NSTX, and START), as this type of device was not part of DB2. However, when removing the spherical tokamaks from STDB5, the scaling law of the energy confinement time gets the following parameters:

$$\tau_{E,th} = 0.09 \cdot I_p^{1.22} \cdot B_t^{-0.04} \cdot \bar{n}_e^{0.15} \cdot P_{l,th}^{-0.67} \cdot R_{geo}^{1.28} \cdot \kappa_a^{0.11} \cdot \epsilon^{-0.01} \cdot M_{eff}^{0.23}, \quad (1.4)$$

resulting in a further decrease in α_R .

Two quick observations can be done from this: (i) the new information suggests that the energy confinement time for the ITER scenario decreases, and (ii) the major radius of a tokamak is not as influential, on the energy confinement time, as the DB2.8 suggests. The latter can be of particular interest since it has been estimated that the cost of a machine scales with $B_t^2 \cdot R_{geo}^3$ [13].

¹For ease of reading, this font will be used to refer to databases only.

²More explained in Chapter 4.

A similar technique to obtain information on the energy confinement time is with the scaling law of the dimensionless physics variables. This implies the application of the Buckingham Π -Theorem, which states that a function that expresses a physical law has the property of generalized homogeneity, meaning that it does not depend on the units of measurement [14]. The method was first applied to tokamak physics by Kadomtsev and a perspective on anomalous transport described by the Fokker-Planck equation was implemented by Connor and Taylor [6], [15]. The result is the following:

$$\omega_i \cdot \tau_{E,th} = \chi_0 \cdot B_t^{\chi_B} \cdot \rho_*^{\chi_\rho} \cdot \beta_t^{\chi_\beta} \cdot \nu_*^{\chi_\nu} \cdot q_{95}^{\chi_q} \cdot \kappa_a^{\chi_\kappa} \cdot \epsilon^{\chi_\epsilon} \cdot M_{eff}^{\chi_M} \quad (1.5)$$

where dimensionless is achieved by multiplying the ion cyclotron frequency $\omega_i = qB_t/M_{eff}$ [15]. Here,

$$\rho_* = \rho_i/a \quad (1.6)$$

is the ion gyroradius ρ_i normalized to the minor radius, ν_* is the ion collision frequency ν_{ii} ,

$$\nu_* = \nu_{ii} \left(\frac{m_i \cdot R_{geo}^3}{q \hat{T} a^3} \right)^{1/2} \cdot q_{cyl} R_{geo}, \quad (1.7)$$

normalized to the bounce frequency of the trapped particles, q_{cyl} is the safety factor at the 95% poloidal flux surface with cylindrical approximation,

$$q_{cyl} = \frac{2\pi}{\mu_0} \cdot \frac{a^2 \kappa_a B_t}{R_{geo} I_p}; \quad (1.8)$$

where I_p is in A, and m_i is the ion mass. By considering the Kadomtsev constraint, one can get the dimensionless regression parameters χ_x , from the engineering regression parameters α_x as [13], [15]:

$$\begin{aligned} \chi_B &= 0, & \chi_q &= \frac{\alpha_R - 4\alpha_I + 3\alpha_P - 2\alpha_n}{5(1 + \alpha_P)}, \\ \chi_\rho &= \frac{2(-3\alpha_R - 3\alpha_I - 9\alpha_P + \alpha_n)}{5(1 + \alpha_P)}, & \chi_\kappa &= \frac{\alpha_k + \alpha_P}{1 + \alpha_P}, \\ \chi_\beta &= \frac{\alpha_R + \alpha_I + 8\alpha_P + 3\alpha_n}{5(1 + \alpha_P)}, & \chi_\epsilon &= \frac{2\alpha_\epsilon - 3\alpha_R + \alpha_I - 5\alpha_P + 2\alpha_n}{2(1 + \alpha_P)}, \\ \chi_\nu &= \frac{-\alpha_R - \alpha_I - 3\alpha_P + 2\alpha_n}{5(1 + \alpha_P)}, & \chi_M &= \frac{5\alpha_M + 3\alpha_R + 3\alpha_I + 4\alpha_P - \alpha_n - 5}{5(1 + \alpha_P)}, \end{aligned} \quad (1.9)$$

which facilitates the shift from the engineering scaling law to the dimensionless scaling law. It is in fact preferable to obtain the estimates of χ_x in this way than direct estimation. This is because ρ_* , β_t , and ν_* are considerably affected by error bars and there is considerable collinearity between the intercept, ϵ , and β_t [12].

Various intriguing analyses can be conducted on the scaling law of the energy confinement time with the updated database. For instance, one can focus on the correlation among variables and how this affects the interpretability of the results. OLS characterizes by assuming that there is no multicollinearity in

the variables and that their uncertainty is negligible with respect to the response variable [16]. Yet, this is not the case for the global H-mode confinement database [12]. Furthermore, work has been done to obtain the regressor parameters α_x using a method that does not neglect the uncertainty in the predictor variables [6]. Others have investigated the energy confinement time with non-linear or non-power scaling forms [17], [18]. However, this project focuses on the dominant causes influencing the decrease of α_R by using data analysis and machine learning algorithms. The aim is to use these algorithms to inspect all the columns available in DB5 and determine if any of them provide insight into explaining the change in α_R .

The proposed workflow involves three steps: first, identifying a subset of records corresponding to shots that contribute to the decrease in α_R ; second, applying data-driven algorithms to this subset to determine common characteristics; and third, analyzing the results of step two for interpretability in terms of tokamak physics. Figure 1.3 illustrates this idea.

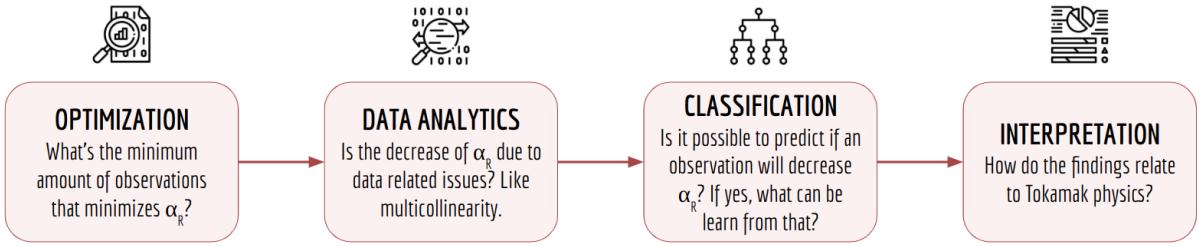


Figure 1.3: Proposed workflow to study the change of the regression parameter α_R in the updated global H-mode confinement database, standard-ELMy subset.

The structure of this report is outlined as follows: Chapter 2 provides an overview of the analyses conducted to identify the minimum subset of variables that contribute to the greatest reduction in α_R . Additionally, this chapter encompasses various regression diagnostics employed to characterize different datasets. Chapter 3 focuses on the classification analyses, including the underlying theory, and examines the variables that are most influential in the algorithms' learning process. This chapter also incorporates the information obtained from Chapter 2. Chapter 4 presents a data-analysis approach to investigate the key findings from Chapter 3 and establish connections with tokamak physics. Finally, Chapter 5 summarizes the main conclusions derived from this project. Appendix A shows the theory needed to understand statements made in Chapter 3.

II

INFLUENTIAL POINTS AND DATA ANALYTICS

This section aims to derive an effective method that identifies the observations that have a substantial influence on α_R . Previously, various algorithms, such as gradient descent, Markov chains, and simulated annealing, were implemented by [19]. The results showed subset sizes ranging from 880 to 1700 with α_R values between 1.1 and 1.2. Nonetheless, instead of subjecting the dataset to complex optimization algorithms, I decided to first assess the impact of influential points and outliers on the new registers in STDB5 using conventional regression diagnostics.

2.1 Regression Diagnostics

Diagnostics techniques make it possible to estimate the influential data and sources of collinearity that may be present in a dataset. However, I will first focus on detecting influential observations. It is common to say that a point greatly influences all regression parameters if it has both high residual and high leverage, as explained shortly [20].

Consider a dataset \mathbf{X} in the form of an $n \times (M + 1)$ matrix¹, where n is the total number of observations and M is the total number of variables used to predict the target variable \mathbf{y} , an n -dimensional column-vector. OLS is a regression model that assumes the target variable,

$$\mathbf{y} = \mathbf{X}\beta + \varepsilon, \quad (2.1)$$

is a parametric function dependent on arbitrary parameters β , a $(M + 1)$ -dimensional column-vector, and Gaussian noise ε , an n -dimensional column-vector often referred to as irreducible error [21]. With OLS, one can predict the target variable $\hat{\mathbf{y}}$ with the optimized parameters $\hat{\beta}$ such that $\hat{\mathbf{y}} - \mathbf{y} = \varepsilon$ is as small as possible. Viewed as a linear algebra problem, one can find the closest vector to \mathbf{y} using Euclidean distances. The solution to this problem is the orthogonal projection of \mathbf{y} onto a subspace \mathcal{R}^n spanned by the columns of \mathbf{X} [21]. Therefore,

$$\hat{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}. \quad (2.2)$$

Now, Eq. (2.2) can be used to estimate the regression parameters α_R when applying the logarithm to Eq. (1.1); namely,

$$\begin{aligned} \log(\tau_{E,th}) = & \log(\alpha_0) + \alpha_I \cdot \log(I_P) + \alpha_B \cdot \log(B_t) + \\ & \alpha_n \cdot \log(\bar{n}_e) + \alpha_P \cdot \log(P_{l,th}) + \alpha_R \cdot \log(R_{geo}) + \\ & \alpha_\kappa \cdot \log(\kappa_a) + \alpha_\epsilon \cdot \log(\epsilon) + \alpha_M \cdot \log(M_{eff}); \end{aligned} \quad (2.3)$$

¹The +1 is to account for the intercept α_0 in Eq. (1.1)

thus, $\hat{\beta} = [\log(\alpha_0), \alpha_1, \dots, \alpha_M]^T$. Having this into account, it is possible to assess the leverage and residual of each point. Leverage is a measure dependent on the mean of a predictor variable and how far an observation is from that mean. In other words, an observation will have high leverage if it is unusually far from the rest observations [22]. Mathematically, the leverage h_i of the i -th observation is

$$h_i \equiv \mathbf{x}_i \left(\mathbf{X}^T \mathbf{X} \right)^{-1} \mathbf{x}_i^T, \quad (2.4)$$

with \mathbf{x}_i denoting the i -th row-vector of the dataset \mathbf{X} [20]. It is common to state that h_i is high if $h_i > (2M + 2)/n$ [22]. The residual is a measure that states how much is a prediction different to the actual target value. There are various ways to estimate this, but here the studentized deleted residual r_i is utilized. The idea is to obtain $\hat{\mathbf{y}}_{i(-i)}$, which denotes the prediction on the i -th observable when this one is removed from the data \mathbf{X} when computing Eq. (2.2); then,

$$r_i \equiv \frac{1}{s_i} (\mathbf{y}_i - \hat{\mathbf{y}}_{i(-i)}), \quad (2.5)$$

where s_i^2 is the estimated variance of $\mathbf{y}_i - \hat{\mathbf{y}}_{i(-i)}$ [23]; with this, it is common to see that the i -th observation is said to have high residual if $|r_i| > 3$; however, one might want to be more strict and reduce the threshold to a more appropriate value to what is being observed with the data [22].

One can also get an insight into the influential points over specific variables by computing the DFBETAS. The idea is to look at the change in regression coefficients when the i -th row is removed and compare the j -column with the original dataset [20], [24]. The estimate is defined as

$$\text{DFBETAS}_{ij} \equiv \frac{\beta_j - \beta_{j(-i)}}{s_i \sqrt{\mathbf{X}^T \mathbf{X}_{jj}^{-1}}}; \quad (2.6)$$

and, it is common to consider that the i -th point is influential on the j -variable if $\text{DFBETAS}_{ij} > 2/\sqrt{n}$; however, this is not a perfect threshold and one can adjust it according to the data [24]. Now, it is useful to have a look at Figure 2.1 showing the Venn Diagram of the databases that will be worked through the project.

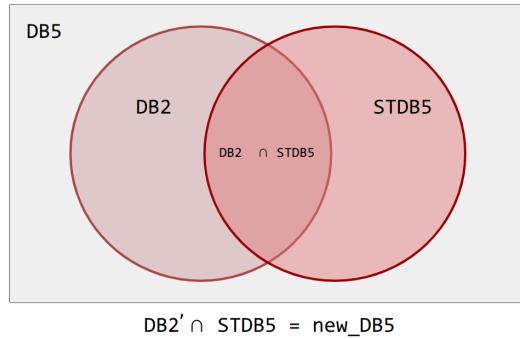


Figure 2.1: Venn Diagram showing the naming of the databases for an easier interpretation.

To determine which observations will undergo regression diagnostics, one new point at a time was selected from `new_DB5` and added to `DB2` to then perform OLS. With this, it is possible to identify the individual points that resulted in a decrease in α_R . The result is shown in Figure 2.2.



Figure 2.2: Variation of α_R given the individual presence of a point in new_DB5. The black line shows the value of α_R when only DB2 is considered. This black line is referred to as *baseline*. The points below the baseline are referred to as *decreased_DB5*. When taking only the *decreased_DB5* with DB2, $\alpha_R = 1.05$.

One can thus focus on the observations that are below the baseline; I will refer to these points as *decreased_DB5*. This database is characterized by 2,544 observations conformed by 12 devices: START, NSTX, MAST, JET, D3D, AUG, AUG with ITER-like-walls (AUGW), JET with ITER-like-walls (JETILW), JT60U, TFTR, COMPASS, and CMOD; with shots done from 1989 to 2017. Figure 2.3 shows the results of applying the regression diagnostics to *decreased_DB5* along with DB2.

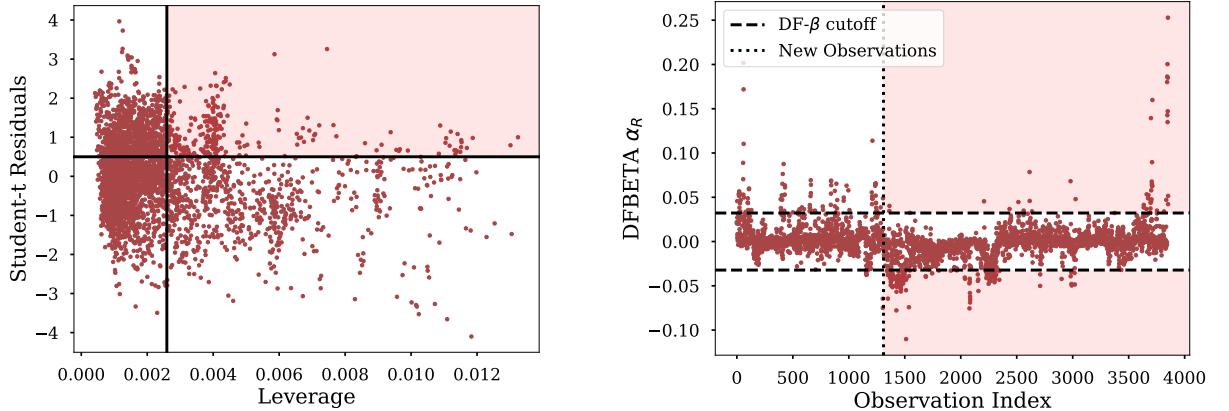


Figure 2.3: LEFT: Influential points to all regressors shown in the pink box according to the concept discussed above. The horizontal and vertical black lines show the cutoff of the Student-t residuals and leverage, respectively. RIGHT: Influential points to α_R shown in the pink areas according to the DFBETAs. DB2 along with *decreased_DB5* were studied. See [25] for code.

In this section, we observed that influential points, as defined earlier, can play a key role in determining the observations that increase α_R . To illustrate this, we evaluated the OLS model on two subsets of data points based on their positions in the leverage-residual plot (Figure 2.3, left): one in the pink area and the other in the white area; the resulting values of α_R were 1.86 and 1.03, respectively. Similarly, when we analyzed the DFBETAs plot (Figure 2.3, right), the values of α_R for the pink and white areas were 1.46 and 1.15, respectively. These results suggest that conventional regression diagnostics may not be entirely reliable in identifying the points that have a significant impact on the reduction of α_R in the confinement time scaling law, especially when using DFBETAs.

2.2 Random Sampling in Decreasing Subset

Another attempted approach, which proved to be the most efficient in terms of both computational resources and achieving the research goal, is random sampling. The idea behind this method is to add the points in `decreasing_DB5` to DB2 in a cumulative manner, without removing the previously added points. This routine allows observing the impact of point grouping on the value of α_R . Figure 2.4 presents the result of this procedure, as well as a close-up view of it.

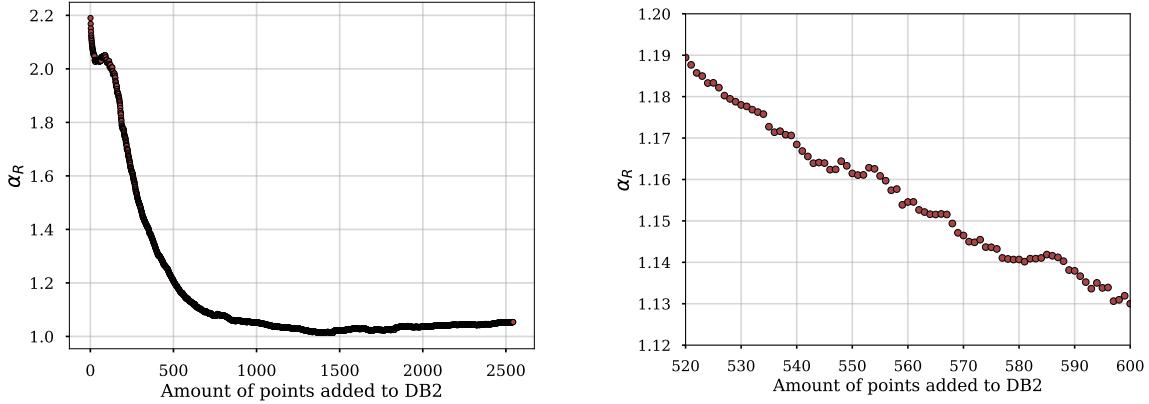


Figure 2.4: LEFT: Change in α_R due to the cumulative behavior of points in `decreasing_DB5`. RIGHT: close-up of the left figure showing that although the added points individually decrease α_R , collectively they increase it.

It is possible to observe that some of the points increase α_R although the overall trending is the reduction of it. From this, one can label the points that increase and decrease α_R in `decreasing_DB5` and then: (i) do a random sampling for all points in the dataset with a higher tendency in picking the decreasing points, and (ii) do a random sampling only of the decreasing points within `decreasing_DB5` to then subject them to OLS, along with DB2. The sampling is performed multiple times, with different sampling subsets, each subset contains unique observations; this is known as bootstrap without replacement [21]. Algorithm 1 depicts the general idea of what was done for both situations.

Algorithm 1 Random sampling to get representative subsets of influential points.

Require: `seeds` = list with 500 different seeds.

```

for seed in seeds do
    for subset_size in range(1, length(dataset)) do
        subset  $\leftarrow$  sampling(decreased_DB5, with random_seed = seed)
        data  $\leftarrow$  subset + DB2
        coefficients  $\leftarrow$  OLS(data)
        alpha_R  $\leftarrow$  coefficients[position = 5]
        plot(alpha_R vs subset_size)
    
```

This approach allows for the generation of representative groups that provide different estimates of α_R based on the subset size. Figure 2.5 shows the resulting groups, along with a close-up of the points of interest after implementing Algorithm 1.

One can quickly appreciate that the random sampling of the decreasing points in `decreasing_DB5` established smaller values of α_R with smaller subset sizes compared with the random sampling on all points in the dataset. Some of the results that might be of interest to study are shown in Table 2.1².

² Although, the observations in DB2 where added to estimate their respective α_R , the resultant named dataset only contains the new observations in STDB, none of them belong to DB2.

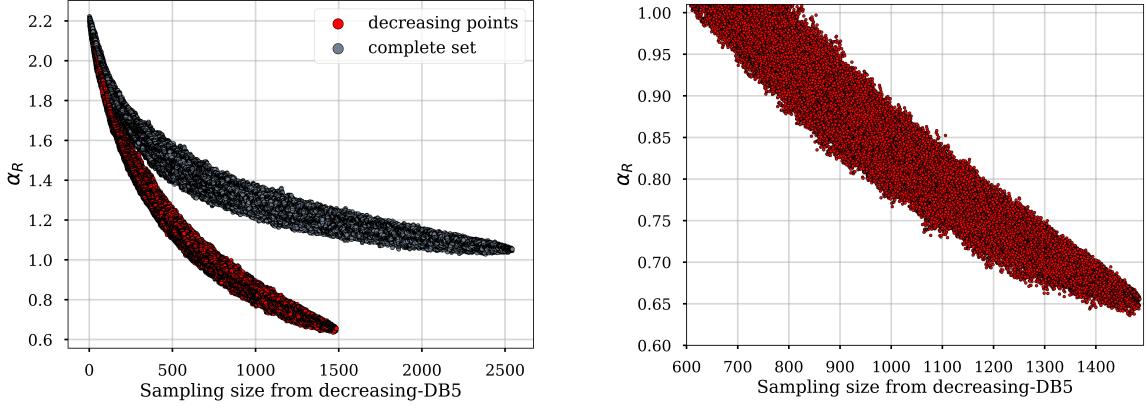


Figure 2.5: LEFT: Change of α_R when sampling different subset-sizes from `decreasing_DB5`. Each of the subsets is added to DB2 to then compute OLS and obtain the respective α_R . RIGHT: close-up to the points of interest: $\alpha_R < 1$.

Table 2.1: Characteristic results of random sampling from the decreasing points in `decreasing_DB5`.

	Smallest Subset for $\alpha_R < 1$	Smallest α_R for subset < 1400	Smallest α_R found
α_R	0.9998	0.6439	0.6357
Subset size	618	1388	1466
Observations decreasing α_R	9.88%	22.20%	23.45%
Dataset Name	<code>small_ds</code>	-	<code>big_ds</code>

Figure 2.6 shows the tokamaks present in `small_ds` (right) and the `big_ds` (left). Notice how, in both situations, spherical tokamaks play a role in influencing α_R . It is also interesting how ASDEX with tungsten walls (AUGW) has a comparative amount of observations decreasing and not affecting α_R in `big_ds`, while the opposite is observed in `small_ds`.

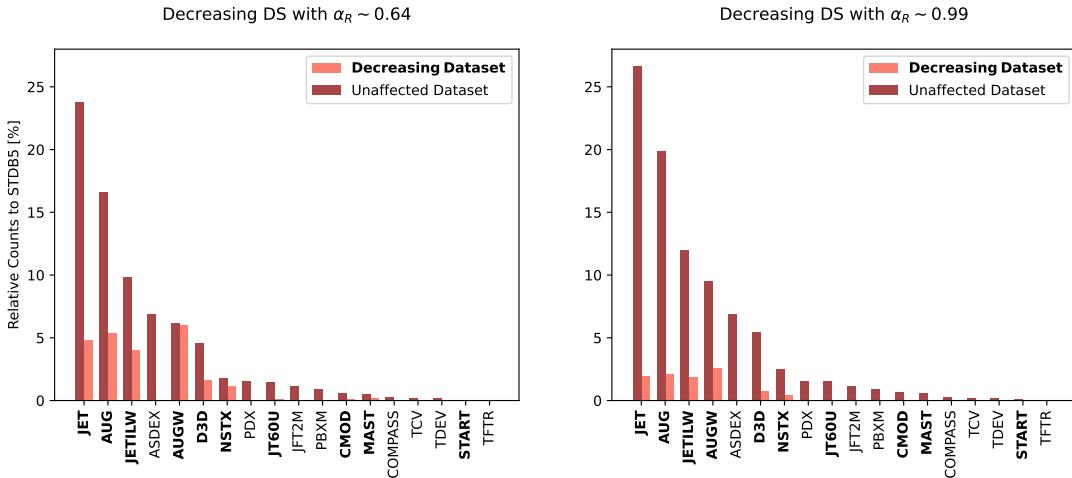


Figure 2.6: LEFT: Counts of tokamaks influencing α_R based on `big_ds`. RIGHT: Counts of tokamaks influencing α_R based on `small_ds`.

The question is: out of all the dataset subsets shown in Figure 2.5 (right), which one will provide the most informative insights into the factors causing the decrease in α_R ? If I were to consider all of them, I would need to study a total of 382,495 subsets. However, to streamline the analysis, I will focus initially on the smallest value found of α_R and the smallest subset size for which $\alpha_R < 1$, since this research aims to discern which columns can yield information into what is decreasing α_R . Table 2.2 shows the

corresponding parameters for estimating $\tau_{E,th}$ based on Eq. (2.1) when utilising the obtained datasets, with the addition of DB2, and when removing them from STDB5.

Table 2.2: Change of parameters in the scaling law of the energy confinement time based on the obtained datasets. All parameters were estimated with all observations present in DB2 for a fairer comparison.

	Scaling	α_0	I_p	B_t	\bar{n}_e	$P_{l,th}$	R_{geo}	κ_a	ϵ	M_{eff}
From big_ds	$\tau_{E,0.64}$	0.10	1.42	0.02	-0.14	-0.53	0.64	-0.002	-0.56	0.13
	$\tau_{E,2.16}$	0.06	0.78	0.24	0.41	-0.75	2.16	0.5	0.79	0.22
From small_ds	$\tau_{E,0.99}$	0.10	1.24	0.11	-0.02	-0.57	0.99	0.14	-0.19	0.12
	$\tau_{E,1.71}$	0.08	1.01	0.12	0.27	-0.71	1.71	0.34	0.32	0.23

Notice that the subset leading to the smaller α_R diminishes the influence of elongation. Further analyses regarding the influence of parameters on the model, within each subset, will be conducted in the subsequent sections.

To conclude the comparison between these two subsets, Figure 2.7 displays the number of shots per dataset according to their respective execution dates. It is evident from the graph that a significant majority of the observations influencing α_R were collected after the 2000s. Moreover, there is no available data for records belonging to the year 2010, this is not only for STDB5 but also for DB5.

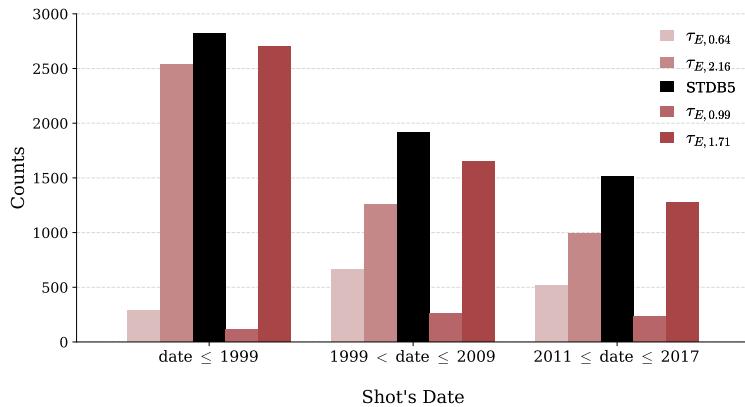


Figure 2.7: Bar plot showing the dates for which the registers were made within each dataset.

2.3 Multicollinearity

One encounters a multicollinearity³ issue when a regression algorithm, such as OLS, struggles to distinguish the effects of one variable from another on the target variable [26]. This issue arises due to significant inter-correlations among the predictor variables [27]. Strong multicollinearity has two main effects: an increase in the standard errors of each coefficient in the model and numerical instability [20], [26]. These consequences might lead to unstable parameter estimation, unreliable models, and weak predictive ability [28]. In other words, the presence of low or moderate multicollinearity does not necessarily imply an issue. However, evaluating the extent of multicollinearity in a dataset will determine whether the model effectively explains how the target variable (in our case, $\tau_{E,th}$) is influenced by each variable [26] (I_p , B_t , \bar{n}_e , $P_{l,th}$, R_{geo} , κ_a , ϵ , and M_{eff}). To determine the presence of multicollinearity in the di-

³Also referred to as *ill conditioning* in numerical analysis [20].

verse available datasets, I will consider the variance inflation factor (VIF), condition index, and variance decomposition.

Variance Inflation Factor (VIF)

The method consists in computing the coefficient of determination R_k^2 of the k -th parameter when regressing it against the remaining explanatory variables [20], [28]. Generally speaking the coefficient of determination R^2 is computed as [20]

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad (2.7)$$

where \bar{y} is the mean value of the target vector. All the other symbols remain with the same interpretation as discussed above. The VIF associated to the k -th regressor parameter is therefore [28]

$$VIF_k = \frac{1}{1 - R_k^2}. \quad (2.8)$$

In the ideal case, $VIF_k = 1$, indicating that there is no collinearity between the k -th regressor parameter and the other variables in the model. When $VIF_k \geq 10$; then, one might have a multicollinearity issue [28]. However, one of the weaknesses of this procedure is that it does not effectively distinguish several coexisting near dependencies [20].

Condition Index

To compute the condition index of all regressor parameters in \mathbf{X} it is necessary to (i) scale \mathbf{X} to have equal (unit) column length and (ii) perform the singular-value decomposition to the scaled (non-centered) matrix [20]. The decomposition is performed as $\mathbf{X} = \mathbf{UDV}^T$; where⁴ $\mathbf{U}^T \mathbf{U} = \mathbf{V}^T \mathbf{V} = \mathbf{I}_M$, and \mathbf{D} contains the nonnegative *singular values, or principal components*, μ and it is diagonal [20]. The obtained singular values are the square roots of the eigenvalues of the covariance matrix; thus, they provide information on the amount of variance explained by each principal component in the data [20]. Furthermore, they are ordered based on the amount of variance they explain. When a high condition number (not to be confused with the condition index) is observed, variables associated with higher principal components are considered of interest when explaining multicollinearity patterns within that dataset [20], [29]. The condition number of the matrix \mathbf{X} is computed as

$$c(\mathbf{X}) = \frac{\max(\mu)}{\min(\mu)} \geq 1. \quad (2.9)$$

The condition index η_k of the k -regressor parameter is obtained as [20]

$$\eta_k = \frac{\max(\mu)}{\mu_k} \quad k = 1, \dots, M. \quad (2.10)$$

⁴The shape the elements are: $\mathbf{X}^{n \times M} = \mathbf{U}^{n \times n} \mathbf{D}^{n \times M} \mathbf{V}^{M \times M}$. In this context, M also accounts for the intercept; hence, $M = 9$ when assessing the scaling law of the energy confinement time.

Notice that the largest condition index is the condition number of the matrix \mathbf{X} . These two values are of great interest when assessing multicollinearity in a dataset, because if $c(\mathbf{X}) \sim 5$ or 10; then, there might be weak dependencies in a dataset. If $c(\mathbf{X}) \sim 30$ or 100; then, there might be moderate to strong dependencies in a dataset. Furthermore, one can also think that there are as many near dependencies as high condition indexes [20].

Variance Decomposition and Associated Π Matrix

Over the presence of high condition indexes, it is recommended to perform the variance decomposition over the variance-covariance matrix $\mathbf{V}(\hat{\beta})$ of the least-squares estimator $\hat{\beta}$ to estimate the damage caused by multicollinearity over the regression estimates [20]. This is done by decomposing $\mathbf{V}(\hat{\beta})$ as [20], [29]

$$\mathbf{V}(\hat{\beta}) = \sigma^2 \left[(\mathbf{U}\mathbf{D}\mathbf{V}^T)^T (\mathbf{U}\mathbf{D}\mathbf{V}^T) \right]^{-1} = \sigma^2 \mathbf{V}\mathbf{D}^{-2}\mathbf{V}^T. \quad (2.11)$$

For the k -th component of $\hat{\beta}$,

$$Var[\beta_k] = \sigma^2 \sum_j \frac{V_{kj}^2}{\mu_j^2}. \quad (2.12)$$

Here, σ^2 is the common variance of the components of ε in Eq. (2.1), μ_j 's are the singular values, and V_{kj} is the (k, j) element in \mathbf{V} [20]. Eq. (2.12) allows identifying unusually high proportions of variance between two or more coefficients by having the singular values in the denominator. From this reasoning, it follows the idea of defining the k, j -th *variance-decomposition proportion* Π_{jk} as the proportion of variance corresponding to the k -th regressor, related by the j -th component of its decomposition in Eq. (2.12) [20]. This influence is observed through the Π matrix, which is calculated as

$$\Pi_{jk} = \frac{\phi_{kj}}{\sum_{j=1}^M \phi_{kj}}, \quad (2.13)$$

where $\phi_{kj} = V_{kj}^2/\mu_j^2$. The ideal case, where no multicollinearity exists in the dataset, would behave as, $\Pi_{ij} = \delta_{ij}$, a Kronecker delta. In other words, the $Var[\beta_k]$ would not be affected by near dependency among the columns of \mathbf{X} [20]. The degradation of a regression estimate due to multicollinearity is evinced when a singular value μ_j associates with two or more coefficients with considerable proportions. The regressors that isolate a singular value indicate that they do not have a collinear dependence with respect to others [20].

2.3.1 Assessing Dependencies in Datasets

In this subsection, I will present the results of conducting the aforementioned multicollinearity tests on four datasets: DB2, DB5, `small_ds`, and `big_ds`. For a comprehensive analysis of `small_ds` and `big_ds`, these datasets have been divided into two subsets: decreasing and unaffected. Each subset contains the respective observations for its specific case. The corresponding labels, and visual representation, for each case, are displayed in Figure 2.8.

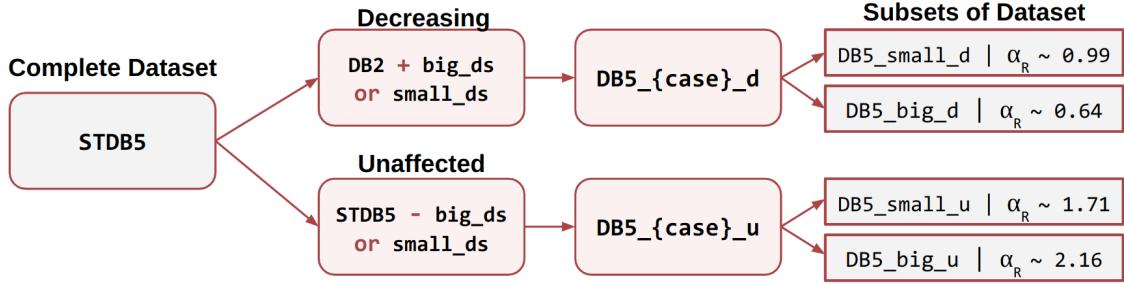


Figure 2.8: Diagram showing the split of `small_ds` and `big_ds` into creating two datasets containing the observations that decrease or does not affect α_R . Notice that resultant subsets are the same that were used to estimate the parameters shown in Table 2.2.

The obtained VIF values for all regressors, categorized by dataset, are presented in Figure 2.9 (left). According to this metric, it is evident that in all cases, the plasma current is a significant contributor to collinearity, followed by the outer radius. When the plasma current is excluded from the dataset, all variables exhibit low VIF values. However, the variable with the highest VIF value shifts from the major radius to the thermal power loss. See Figure 2.9 (right).

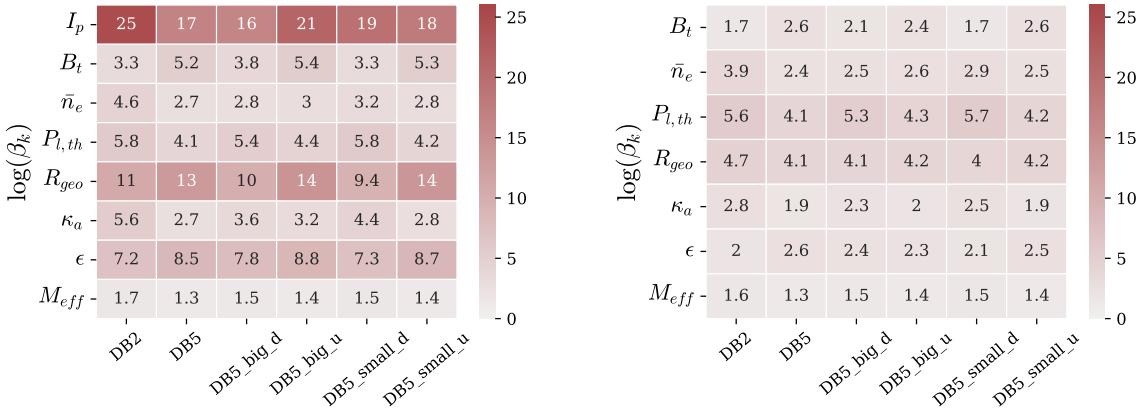


Figure 2.9: LEFT: VIF scores of all regressors. RIGHT: VIF scores of regressors after removing the plasma current. It is considered that a high $VIF \geq 10$.

Furthermore, the condition number and the Π matrix was computed for all datasets. All cases showed a high condition number, meaning that all of them are likely to show multicollinearity issues. Moreover, all datasets showed three condition indexes ranging [10,20], one condition index ranging [25,35], and one (also their condition number) ranging [46, 58].

Figure 2.1 shows the results implemented to DB2 and DB5. In both datasets, the effective mass showed an isolated principal component, meaning that this variable is not collinear with the others. Almost the same behaviour is observed for the intercept, except that in DB5, its variance is almost split in half by two principal components. All other variances share various principal components. However, the singular value μ_8 accounts for more than 60% of $Var(I_p)$, $Var(B_t)$ and $Var(\epsilon)$, with the latter being 99% in both DB2 and DB5. Figure 2.11 show the results for the two subsets resulting from `big_ds`. In this subset, the variance of the effective mass is isolated to mostly one principal component. A similar pattern is observed for μ_8 , where it explains a significant portion of the variance in I_p , B_t , \bar{n}_e , $P_{l,th}$, R_{geo} , κ_a , and primarily ϵ . Notably, in the unaffected dataset compared to the decreasing dataset, the influence of μ_8 increases. Figure 2.12 presents the results of the analyses conducted on `small_ds`. A similar pattern is observed, although the increase in influence for μ_8 is not as significant as in the previous case. However, it is worth noting that the percentage of variance explained by κ_a drops from approximately 30% in the decreasing

dataset to around 15% in the unaffected dataset.

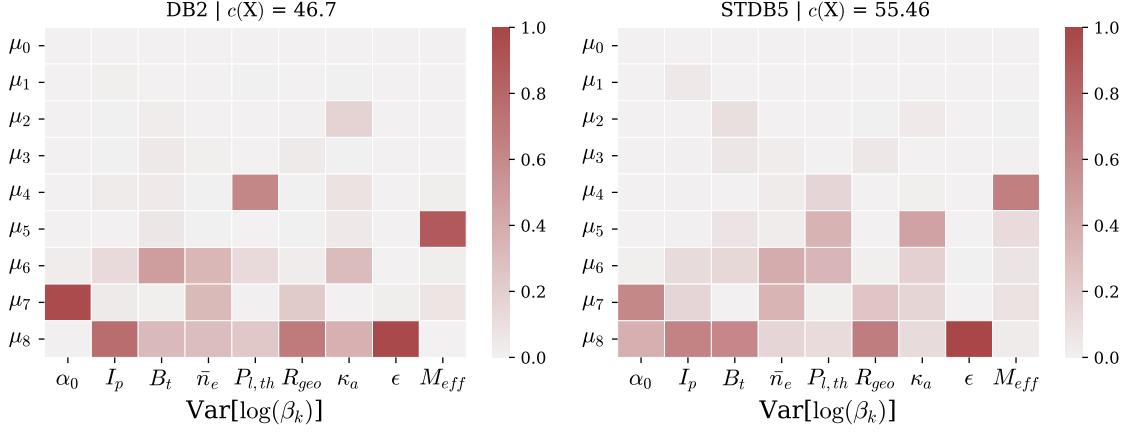


Figure 2.10: Π matrix for DB2 (left) and DB5 (right) with their corresponding condition number $c(\mathbf{X})$, for all variances associated to the regressor variables in Eq. (2.1).

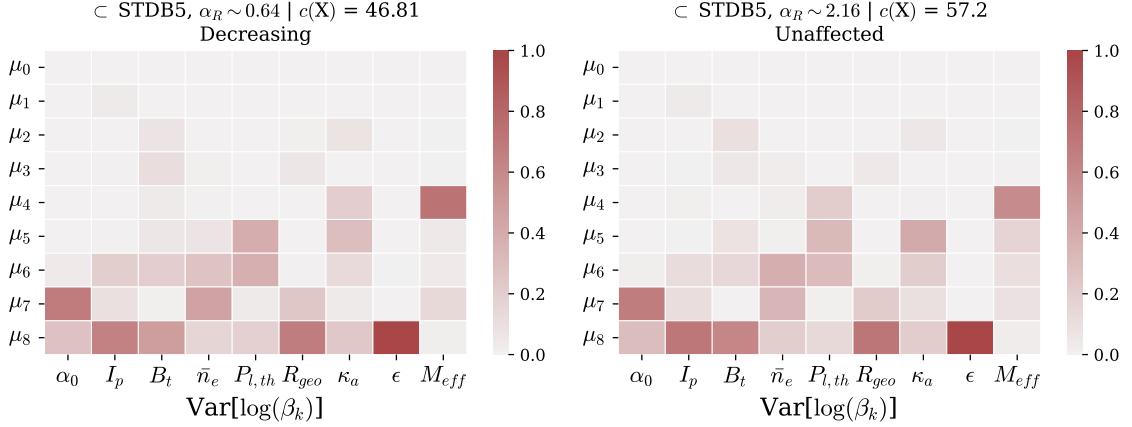


Figure 2.11: Π matrix for observations that decrease α_R (left) and does not affect α_R (right), based on `big_ds` with their corresponding condition number $c(\mathbf{X})$, for all variances associated to the regressor variables in Eq. (2.1).

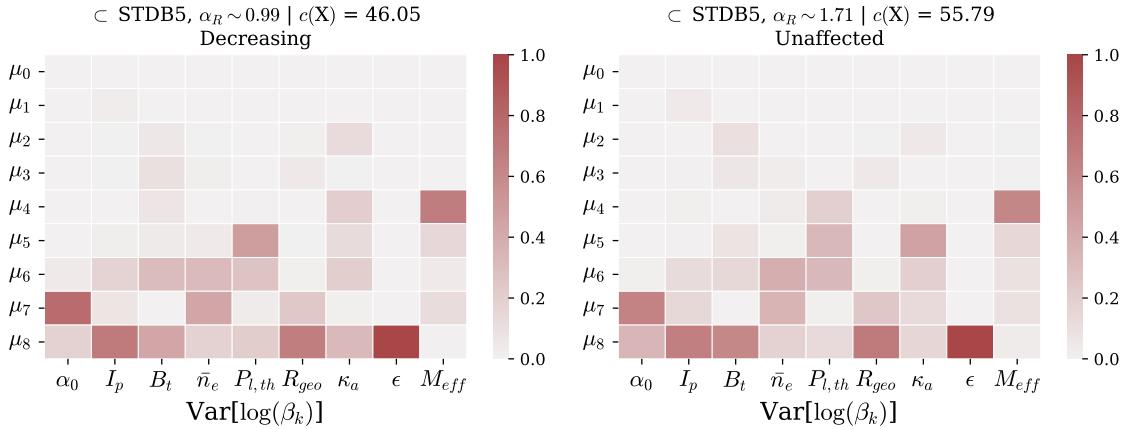


Figure 2.12: Π matrix for observations that decrease α_R (left) and does not affect α_R (right), based on `small_ds` with their corresponding condition number $c(\mathbf{X})$, for all variances associated to the regressor variables in Eq. (2.1).

Overall, similar patterns and behaviours are observed across all datasets, including the total number of high η_k present in the data. It is worth mentioning that the inclusion of spherical tokamaks in the dataset

has a slight mitigating effect on multicollinearity within STDB5. Removing these devices from the dataset results in $c(\mathbf{X}) = 57.93$.

2.4 Model Comparison

Multivariate models tend to be updated when more data is available. One can use statistical tests to compare models and assess the performance of the multivariate model given the new data, removal or addition of variables [30]. In this section, I will use the F-test to compare nested models; these are models where one is a special case of the other, for instance, a reduced model from a full model [31]. Here, our full model is described by Eq. (2.1) in the log-space, and the reduced model is the removal of at least one of its variables. To compute the F-statistic, one needs the sum of square error (SSE), being

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2, \quad (2.14)$$

one can then compute its value for the specific case to obtain

$$\Delta SSE = SSE_r - SSE_f. \quad (2.15)$$

Here, the subscripts r, f denote the reduced and the full model, respectively. The mean square error (MSE) is the SSE divided by the number of observations n in the dataset. The F-statistic, or F-value, is then

$$F = \frac{1}{\Delta M} \cdot \frac{\Delta SSE}{MSE_f}, \quad (2.16)$$

where ΔM is the number of coefficients being tested, also referred to as the numerator degrees of freedom ν_1 . The denominator degrees of freedom is $\nu_2 = n - M$. These two are important when computing the P-value [31]. The P-value, denoted as $Pr(F_{\nu_1, \nu_2} \geq F)$, represents the probability of observing the obtained F-value based on the F-distribution with degrees of freedom ν_1 , and ν_2 . Usually, it is considered that having $F \geq 2.5$, or $P \leq 0.05$, is enough to consider that the reduced model is statistically significantly different than the full model and that it performs better. This type of analysis is also referred to as ANOVA (analysis of variance) test [32]. Table 2.3 show the F- and P-values for DB2, and STDB5. Table 2.4 show the same results for the two subsets that follow from `small_ds`, and `big_ds`, as explained in Figure 2.8.

The results indicate that, as anticipated, no variable should be eliminated when using the DB2 dataset. However, for STDB5, it may be acceptable to remove the inverse aspect ratio without significantly degrading the model's performance. For the other subsets of STDB5, it is observed that removing the elongation and toroidal magnetic field may not have a negative impact on the model when utilizing `DB5_big_d`. In the case of `DB5_small_d`, only the averaged-line electron density should be considered for removal. For the remaining unaffected datasets, all variables should be retained. Furthermore, when the elongation is removed from the subset with $\alpha_R \sim 0.64$, the value of $Pr(> F)$ increases from 0.32 to 0.42. When both κ_a and B_t are removed from the same subset, all the other variables maintain a $Pr(> F)$ value of 0. It is interesting to note that none of the subsets suggests that the removal of the major radius may not degrade the model.

Table 2.3: ANOVA test applied to DB2, and STDB5.

		DB2		DB5	
Removed	F	Pr(>F)	F	Pr(>F)	
I_p	961.58	0.0	4809.57	0.00	
B_t	138.99	0.0	25.79	0.00	
\bar{n}_e	494.28	0.0	332.97	0.00	
$P_{l,th}$	2674.97	0.0	10024.60	0.00	
R_{geo}	2022.43	0.0	3221.36	0.00	
κ_a	94.67	0.0	94.70	0.00	
ϵ	131.14	0.0	2.96	0.09	
M_{eff}	36.51	0.0	157.27	0.00	

Table 2.4: ANOVA test applied to subsets of STDB5 that result in cases where observations decrease or do not affect α_R w.r.t. α_R in DB2.

Removed	Decreasing $\alpha_R \sim 0.64$		Unaffected $\alpha_R \sim 2.16$		Decreasing $\alpha_R \sim 0.99$		Unaffected $\alpha_R \sim 1.71$	
	F	Pr(>F)	F	Pr(>F)	F	Pr(>F)	F	Pr(>F)
I_p	4165.11	0.00	2370.15	0.0	2149.90	0.000	3757.01	0.0
B_t	1.011	0.32	300.46	0.0	18.89	0.000	69.15	0.0
\bar{n}_e	85.69	0.00	1971.23	0.0	1.23	0.269	752.88	0.0
$P_{l,th}$	2017.40	0.00	14937.77	0.0	1609.65	0.000	11206.25	0.0
R_{geo}	294.38	0.00	7450.69	0.0	471.16	0.000	4404.12	0.0
κ_a	0.002	0.97	350.36	0.0	10.45	0.001	144.63	0.0
ϵ	136.93	0.00	507.59	0.0	11.20	0.001	77.07	0.0
M_{eff}	25.50	0.00	182.73	0.0	15.86	0.000	179.70	0.0

In this chapter, I have demonstrated how bootstrapping sampling can be used to find representative subsets that decrease α_R , without the need for complex optimization algorithms. Conventional regression diagnostics were also implemented but failed to discern the observations that reduced α_R . The smallest α_R found through sampling was 0.6357, with a subset size of 1466. It is worth noting that the order of points being added to DB5 from decreasing_DB5, to create Figure 2.4 (left), does not influence the overall result, but it does change the shape of the plot. Furthermore, I have examined the presence of multicollinearity among different subsets and investigated whether it is possible to remove a variable from the model presented in Eq. (2.1) without detrimental effects, given the updated observations. The analyses revealed that R_{geo} plays a crucial role in estimating $\tau_{E,th}$, and it was found that multicollinearity may not be solely responsible for the decrease in α_R when utilizing STDB5. This is evident from the fact that the division of the dataset into decreasing and unaffected subsets did not exhibit a significant reduction in multicollinearity; this absence of variability within the split datasets emphasizes the need to explore potential physical factors contributing to the decrease in α_R .

III

MACHINE LEARNING ALGORITHMS

Machine learning refers to computer programs that learn and make decisions based on data, regardless of the field of application; this sets it apart from traditional data analysis [21]. Machine learning can be used to guide research when mathematical expressions are not available or when data is limited. For instance, in drug discovery, these algorithms are used to identify molecules with specific properties, such as binding affinity to a target protein, even when the underlying mechanism of action is not well understood [33]. Astronomy [34] and neuroscience [35] are other fields where machine learning is implemented to recognize patterns and correlations in data, leading to new areas of research or refinement of existing theories. In this chapter, I will use supervised machine learning algorithms to investigate the causes that lead to a decrease in α_R . This will be based on the subsets obtained in the previous chapter.

3.1 Feature Selection

One of the challenges when implementing any machine learning algorithm is feature selection, the process of deciding which columns of a dataset should be used so that the algorithm can learn better and faster from them. Moreover, identifying and extracting the right features becomes more complex as the number of columns in the dataset increases, since adding or removing them could reduce the algorithm's learning quality [21]. To address this issue, I have (i) identified which of all the variables available in DB5 can help understand why there is a reduction in α_R , (ii) utilized the concept of entropy in information theory to identify which of these variables contain more information, (iii) considered relevant research to decide on a set of variables that will yield more insight into the reduction of α_R , and (iv) studied the different resultant subsets for multicollinearity.

3.1.1 All Variables of Interest

In DB5, there are 192 columns containing information on the tokamaks, including divertor and wall materials, plasma characteristics, heating mechanisms, instabilities, impurities, power, and more [11]. However, since I am using the standard version, not all of the columns have complete values, and not all of the columns are relevant. Tables 3.1 to 3.7 show the description [11] of 47 variables that I have considered to be interesting for this project, based on the knowledge I have gained through this master programme. In all tables, **bold features** represent the variables provided by the research group, not found in [11], and underline features are categorical data.

To clean STDB5, I have applied the pipeline shown in Figure 3.1. The cleaned dataset, which includes the 47 variables of interest and all rows from STDB5, will be referred to as `clean_DB5`. In subsequent references to `small_ds` or `big_ds` (see Table 2.1), their cleaned versions will be used.



Figure 3.1: Pipeline showing the criteria to clean STDB5. The one-hot encoding creates a binary vector, for each category in the column, with 1 if the observation has that observation and 0 otherwise [36].

Table 3.1: Variables of interest regarding plasma characteristics.

Feature	Description	Feature	Description
BEIMHD	Beta Shafranov	MEFF	Effective atomic mass
BETASTAR	Plasma pressure normalised to B_t	NUSTAR	normalised Ion collision frequency
CONFIG	Plasma configuration	PREMAG	Flag for startup: with or without pre-magnetization current
DWDIA	Time rate of change of the total plasma stored energy	Q95	Plasma safety factor at the 95% poloidal flux surface
EPS	Inverse aspect ratio	RHOSTAR	normalised Ion Gyroradius
IP	Plasma current	TORQ	Torque on plasma due to NBI
KAREA	Plasma elongation	VOL	Plasma volume
LCOULOMB	Coulomb Logarithm $\log_e(\Lambda) = 30.9 - \log_e(\bar{n}_e^{0.5}/\hat{T})$	WMHD	Total plasma energy (MHD equilibrium)

Table 3.2: Variables of interest regarding heating.

Feature	Description	Feature	Description
AUXHEAT	Type of auxiliary heating	PELLET	Pellet material if injected
ECHMODE	Mode of ECRH waves	PICRH	ICRH power absorbed by the plasma
ENBI	Neutral beam energy weighted by power	PNBI	Total NBI power minus shine through
ICSCHEME	ICRH heating scheme	POHM	Total Ohmic Power
PECRH	ECRH power absorbed by the plasma	PRAD	Total radiated power as measured by Bolometer

Table 3.3: Variables of interest regarding impurities.

Feature	Description
<u>EVAP</u>	Evaporated material to cover the vessel
ZEFF	Line average plasma effective charge, from Bremsstrahlung
ZEFFNEO	Plasma effective charge, from neo-classical resistivity

Table 3.4: Variables of interest regarding tokamaks' characteristics.

Feature	Description	Feature	Description
AMIN	Horizontal plasma minor radius	<u>LIMMAT</u>	Limiters' material
BT	Vacuum toroidal magnetic field at R_{geo}	<u>TOK</u>	Tokamak's name
DIVMAT	Material of divertor tiles	<u>WALMAT</u>	Walls' material

Table 3.5: Variables of interest regarding power loss and ELMs.

Feature	Description	Feature	Description
BEIMHD	NBI power that is lost from the plasma through charge exchange and unconfined orbits	<u>ELMTYPE</u>	Type of ELMs
PLTH	Estimated loss power corrected for charge exchange and unconfined orbit losses	<u>ELMFREQ</u>	ELM frequency

Table 3.6: Variables of interest regarding temperature.

Feature	Description
TAV	Total volume average temperature
TEV	Total volume averaged electron temperature
TIV	Total volume averaged ion temperature

Table 3.7: Variables of interest regarding particles.

Feature	Description	Feature	Description
NEL	Central line average electron density	OMEGACYCL	Ion Cyclotron Frequency $\omega_i = qB_i/M_{eff}$
NESOL	Electron density in scrape-off layer	WFFORM	Total fast ion energy due to NBI
WFICFORM	Total fast ion energy due to ICRH estimated from approximate formula		

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While all these variables may contain valuable information, it does not necessarily mean that an algorithm will perform optimally when utilising all of them. In fact, there are instances where it is desirable to reduce the number of features and only include the most representative ones. This process is often referred to as feature engineering. Additionally, it has been observed that as the number of features in a model increases, the number of required observations grows exponentially in order to achieve satisfactory performance. This phenomenon is commonly known as the "curse of dimensionality" [37]. Therefore, it becomes crucial to identify a subset of the relevant features that can potentially reduce the model's complexity and improve its overall performance.

3.1.2 Entropy Variables

By considering features as random variables, it is possible to use the concept of entropy in information theory to estimate the amount of order or information in a feature [38]. The entropy of a random variable Z is defined as [39]:

$$E(Z) = - \sum_z p(Z = z) \cdot \log(p(Z = z)). \quad (3.1)$$

Here, $p(Z = z)$ represents the prior probability of z . The units of entropy depend on the logarithm being used, if it is \log_2 then the units are bits, which represent the number of bits¹ required to characterize the random event [41]. However, there is no specific expression for the probabilities of all the features of interest, it is possible to approximate Eq. (3.1) using the similarity of observation, which directly depends on the distance between them [38]. To estimate the similarity between two observations S_{ij} for numerical data, euclidean distance is implemented as

$$S_{ij} = \exp(-\gamma \cdot D_{ij}), \quad D_{ij} = \left[\sum_{k=1}^M \left(\frac{x_{ik} - x_{jk}}{\max(F_k) - \min(F_k)} \right)^2 \right]^{1/2}, \quad (3.2)$$

where D_{ij} being a $n \times n$ matrix. Here, F_k represents the column vector belonging to the k -th feature, out of the total M features. And, x_{ik} (or x_{jk}) is the i -th (or j -th) row, and the k -th column in \mathbf{X} . Finally, γ is a parameter which can be tuned according to the problem at hand. It is common to set $\gamma = 0.5$ [38]. For categorical features, the similarity is computed through the Hamming distance² as [38]:

$$S_{ij} = \frac{1}{M} \sum_{k=1}^M \delta_{ij}(x^k); \quad \text{with } \delta_{ij}(x^k) = \begin{cases} 1, & \text{if } x_i^k = x_j^k \\ 0, & \text{if } x_i^k \neq x_j^k \end{cases}. \quad (3.3)$$

From this, it is possible to evaluate the entropy of a dataset³ as [38]:

$$E = - \sum_{\substack{i,j=1 \\ i \neq j}}^N \left[S_{ij} \log(S_{ij}) + (1 - S_{ij}) \log(1 - S_{ij}) \right]. \quad (3.4)$$

To estimate the importance of a feature's presence in a dataset in terms of information, one can compute the entropy of the dataset with the missing k -th feature E_{-F_k} and compare this instance to another one missing a different feature. For example, if $E_{-F_1} > E_{-F_2}$, one can say that feature 1 is more important than feature 2, as the former imposes more structure in the database [38]. The idea shown in Algorithm 2 to rank the feature importance of `small_ds` and `big_ds`, was implemented.

Algorithm 2 Ranking features' importance based on entropy.

Require: `entropy_features` = empty one-dimensional array of size M

```

for feature in columns(clean_dataset) do
    data  $\leftarrow$  clean_dataset without feature
    entropy_k  $\leftarrow$  get_entropy(data)
    entropy_features.append(entropy_k)
ordered_features  $\leftarrow$  sort_values(entropy_features)

```

¹If \log_e , units are nats. If \log_{10} , ban. And, if $10\log_{10}$, deciban (db) [40].

²In case the reader is interested, one can simply compute $\delta_{ij}(x^k)$ in Python with:

`np.frompyfunc(lambda x,y: x==y, 2, 1).reduce(np.array(np.meshgrid(F_k, F_k)))`

³In the case of $S_{ij} = 0$, it is considered that $0\log(0) = 0$.

The result of this method is shown in Figure 3.2. Notice that the entropy associated with the dataset for all variables, with one missing column, results in high values of bits. This is just a reflection that the dataset itself is extraordinarily disordered with high levels of uncertainty [42]. Moreover, the information contributed by the categorical data is less than the numerical data, this can also be observed in Figure 3.2, along with Table 3.8. When implemented in Python, the result is the following when printing the ordered features from the most important to the less important.

```
>>> print(ordered_features)

['WFICFORM', 'WFFORM', 'RHOSTAR', 'ZEFFNEO', 'DWDIA', 'BETASTAR', 'POHM', 'NEL',
 'NUSTAR', 'EPS', 'TAV', 'PFLOSS', 'WMHD', 'Q95', 'MEFF', 'PLTH', 'LCOULOMB',
 'OMEGACYCL', 'KAREA', 'PICRH', 'TIV', 'PRAD', 'TEV', 'PNBI', 'PECRH',
 'ELMFREQ', 'IP', 'ENBI', 'AMIN', 'ZEFF', 'TORQ', 'NESOL', 'BT', 'BEIMHD',
 'VOL', 'TOK', 'WALMAT', 'EVAP', 'PREMAG', 'LIMMAT', 'DIVMAT', 'ELMTYPE',
 'ECHMODE', 'ICSHEME', 'PELLET', 'CONFIG', 'AUXHEAT']
```

Meaning that the less important in providing information, is the type of auxiliary heating used during the shot, and the most important is the total fast one energy due to ICRH. It is also interesting to note that most of the categorical data do not contribute significantly to providing information. From this, we can then take the first 16 most important variables in terms of entropy, and subject that subset to analysis. In this case, the *entropy variables* will be: WFICFORM, WFFORM, ZEFFNEO, RHOSTAR, DWDIA, BETASTAR, POHM, NEL, WMHD, TAV, NUSTAR, EPS, PFLOSS, Q95, PLTH, and LCOULOMB.

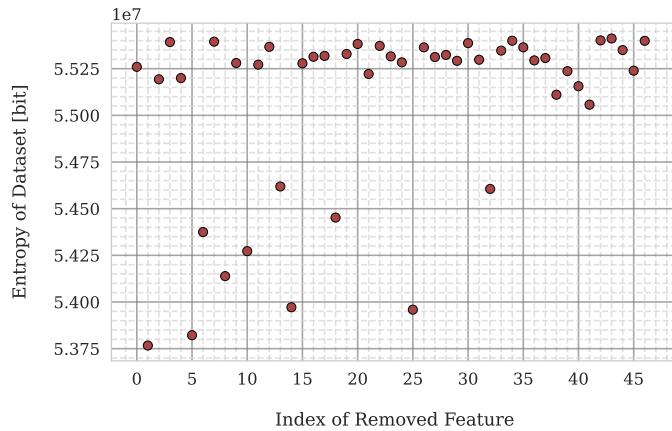


Figure 3.2: Result of applying Algorithm 2 to the 47 variables of interest in `big_DB5`; the same output resulted when applying it to `small_DB5`, despite having 848 fewer observations which may have made it more ordered.

Table 3.8 shows the labels of the index of the removed feature.

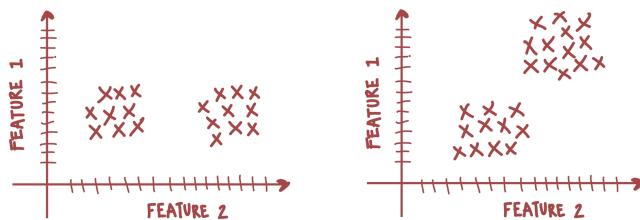


Figure 3.3: Simple drawing showing the comparison between two situations to understand feature dependence for finding ordered groups.

Note that the presence of certain variables can overshadow or enhance the importance of others. For example, a single feature can contain ordered groups by itself, as shown in Figure 3.3 (left), while other features may need to be combined to obtain an ordered group, as shown in Figure 3.3 (right).

While the Entropy method considers dependence on other features, it does not evaluate the best subset of features. Due to the many possible feature subsets that can be assessed from the 47 variables of interest, alternative methods have been implemented to identify relevant subsets that provide insights into the factors affecting the decrease in α_R .

Table 3.8: Numbering of variables in Figure 3.2.

0 - AMIN	12 - ELMTYPE	24 - PECRH	36 - Q95
1 - AUXHEAT	13 - ENBI	25 - PELLET	37 - RHOSTAR
2 - BEIMHD	14 - EPS	26 - PFLOSS	38 - TAV
3 - BETASTAR	15 - EVAP	27 - PICRH	39 - TEV
4 - BT	16 - ICSHEME	28 - PLTH	40 - TIV
5 - CONFIG	17 - IP	29 - PNBI	41 - TOK
6 - DIVMAT	18 - KAREA	30 - POHM	42 - TORQ
7 - DWDIA	19 - LCOULOMB	31 - PRAD	43 - VOL
8 - ECHMODE	20 - LIMMAT	32 - PREMAG	44 - WALMAT
9 - ELMFREQ	21 - MEFF	33 - Q95	45 - WFFORM
10 - ELMTYPE	22 - NEL	34 - RHOSTAR	46 - WMHD
11 - ENBI	23 - NESOL	35 - TAV	

3.1.3 Research Variables

During the last year of my master, I attended a two-week workshop, at CEA Cadarache, that required me and my team to estimate the toroidal magnetic field B_t [T] and the radius R_{geo} [m] of a tokamak given the target fusion power P_{fus} [MW] and fusion gain Q . To solve this issue, it is possible to create a system of non-linear equations [43]; such as:

$$R_{geo}^3 B_t^4 = \frac{P_{fus} C_\beta^2 q_{95}^2}{C_{fus} C_I^2 \kappa_a \epsilon^4 \beta_N^2}, \quad (3.5)$$

and

$$R_{geo}^{-\gamma_R} \cdot B_t^{-\gamma_B} = C \cdot \Gamma(Q) \cdot \alpha_0 \cdot P_{fus}^{\alpha_p} \cdot M_{eff}^{\alpha_M} \cdot \kappa_a^{\alpha_\kappa} \cdot \epsilon^{\gamma_\epsilon} \cdot n_N^{\alpha_n} \cdot q_{95}^{-\gamma_l} \cdot \beta_N, \quad (3.6)$$

where $\Gamma(Q)$, β_N , n_N , γ_R , γ_B and the constants C , C_I , C_{fus} , C_β are defined through the derivation (see Appendix A) as properties of the tokamak are established. The main takeaway of this research is that one can get an expression where the energy confinement time $\tau_{E,th}$ scales with four engineering variables: line average electron density \bar{n}_e , temperature of the plasma \hat{T} , outer radius R_{geo} , and toroidal magnetic field B_t . Hence, I can consider this set of variables as a subset of interest. But, for completeness, I have also added Kadomtsev's dimensional analysis, which expects the system to be governed by ρ_* , ν_* , and β_t [13]. Therefore, I have decided that the *research variables* are: NEL (\bar{n}_e), TAV (\hat{T}), BT (B_t), RHOSTAR (ρ_*), NUSTAR (ν_*), and BETASTAR (β_t).

3.1.4 Low Multicollinearity Variables

To assess the amount of multicollinearity in the variables of interest, I have implemented the same techniques explained in the previous chapter to `clean_DB5`. The result is shown in Figure 3.4.

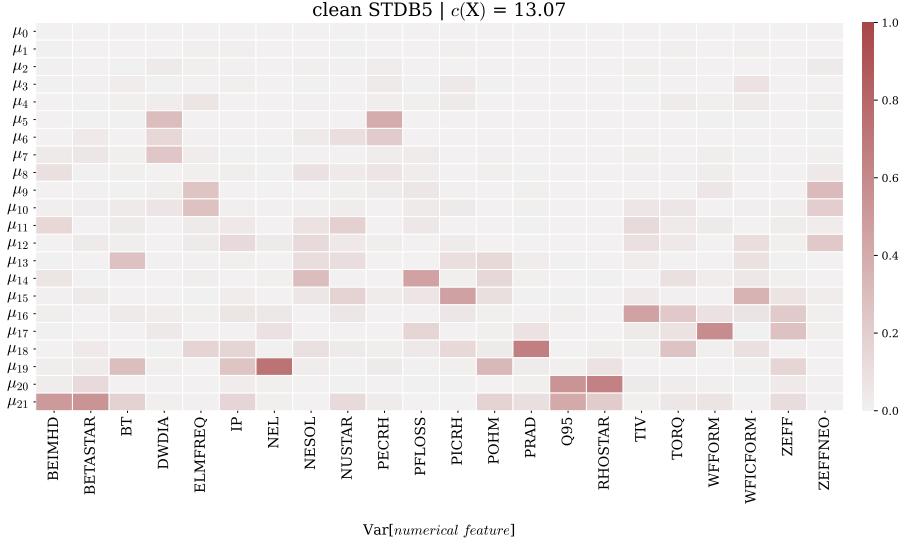


Figure 3.4: Π matrix and condition number for all numerical features of interest.

The VIF of PLTH and PNBI were 4200 and 3600, respectively. To derive a subset of variables with low multicollinearity, I systematically removed one variable at a time and recalculated the condition number along with the VIF of each variable until they stopped being too high. To reach a condition number of 13.07 and a maximum VIF of 14, the following variables were removed: PLTH, AMIN, LCOULOMB, KAREA, EPS, MEFF, TAV, ENBI, PNBI, OMEGACYCL, TEV, VOL, WMHD. Hence, the resultant variables with low multicollinearity are:

```
>>> print(low_multicollinearity_features,)

['BEIMHD', 'BETASTAR', 'BT', 'DWDIA', 'ELMFREQ', 'IP', 'NEL', 'NESOL', 'NUSTAR',
 ↓ 'PECRH', 'PFLOSS', 'PICRH', 'POHM', 'PRAD', 'Q95', 'RHOSTAR', 'TIV', 'TORQ',
 ↓ 'WFFORM', 'WFICFORM', 'ZEFF', 'ZEFFNEO']
```

made of 22 numerical features.

3.2 Classification

As previously mentioned, machine learning algorithms are trained to learn from data in order to make predictions or decisions. If the algorithm predicts numerical data, it is known as regression, such as OLS. On the other hand, if the algorithm predicts classes or categorical data, it is known as classification. Both regression and classification are forms of supervised machine learning, meaning that the data must include an output variable y for the algorithm to learn from the input columns X . The goal of the algorithm is to learn how the input relates to the output to correctly predict y for new inputs that it has never seen [21]. Given this information, it is possible to use the results from Chapter 2 to add a new column to `clean_DB5` containing the labels that do not affect or decrease α_R , labelled as 0 and 1 respectively. Observations belonging to either `small_ds` or `big_ds` (depending on the case being studied) will be labelled with 1.

There are numerous algorithms available for classification, some of which may or may not be well-suited for the problem at hand. Certain algorithms, referred to as "data-hungry" require large amounts of data and tend to perform well in fields such as social media, where a vast amount of data is generated daily. However, these algorithms can be challenging to implement in academic research as acquiring more data is typically expensive or unattainable [44], [45]. On the other hand, there are algorithms that perform exceptionally well with a small amount of data because they require the inverse of a certain matrix, which can be computationally expensive [21].

3.2.1 Imbalanced Data

For this project, I have adopted the step-by-step framework proposed by [46], which is designed to handle imbalanced data classification problems. The framework focuses on selecting a classifier that performs well in predicting the minority class, which in our case is the class that decreases α_R . The author suggests first focusing on choosing the correct metric and then using that to test various algorithms.

Various metrics evaluate different aspects of the algorithm. For example, a particular metric can enhance the performance in predicting all classes, the majority class, or the minority class; selecting the wrong metric means selecting an incorrect algorithm for solving a specific problem [46]. Since we need to predict two labels, 0 and 1, we have a binary classification problem; various metrics for this type of problem can be obtained through a tool known as "confusion matrix", see Figure 3.5. Table 3.9 shows some of the most common metrics that can be obtained through a confusion matrix.

To use a confusion matrix, the data must be split into two sections: one for training the algorithm, and the other for validating its performance on unseen observations. Typically, the validation dataset comprises 20% to 50% of the complete dataset, depending on the amount of available data [21]. For this project, I created a validation dataset by stratified random⁴ sampling 30% of clean_DB5, with its corresponding labels.

		Labeled as decrease [1]	Labeled as unaffected [0]	
		True Positive (TPs)	False Positive (FPs)	Precision
Predicted Decrease	Labeled as decrease [1]	True Positive (TPs)	False Positive (FPs)	$\frac{TPs}{TPs + FPs}$
	Labeled as unaffected [0]	False Negatives (FNs)	True Negatives (TNs)	
Predicted Unaffected		Recall		$\frac{TPs}{TPs + FNs}$

Figure 3.5: Confusion matrix for a binary class and two metrics. This is a tool to obtain different metrics to evaluate an algorithm, here showing for precision and recall. The minority class is referred to as positive. See Table 3.9 for more metrics.

It is important to mention that all classifiers make use of a threshold, whose values $\in [0, 1]$, to make decisions or predictions. The choice on this threshold directly impacts the performance of the algorithm, if it is too high, the classifier will almost never predict the positive class, and vice versa [21].

⁴This means that there is the same amount of classes in the training dataset as in the validation dataset.

Table 3.9: Some of the obtainable metrics from a confusion matrix [21], [46]. Remember that n is the total number of observations in a dataset.

Metric	Formula	Description
Misclassification Rate	$\frac{FNs + FPs}{n}$	Fraction of predictions being incorrect
Accuracy	$\frac{TNs + TPs}{n}$	Complement of misclassification rate
Precision	$\frac{TPs}{TPs+FPs}$	Fraction of predicted positives actually being positive
Recall	$\frac{TPs}{TPs+FNs}$	Fraction of actual positives correctly predicted
Fall-out	$\frac{FPs}{FPs+TNs}$	Probability of false alarm
Specificity	$\frac{TPs}{FPs+TNs}$	Compliment of fall-out
False discovery rate	$\frac{FPs}{FPs+TPs}$	Fraction of incorrect positive predictions
False negative rate	$\frac{FNs}{FNs+TPs}$	Fraction of actual positive incorrectly classified
False omission rate	$\frac{FNs}{FNs+FPs}$	Fraction of incorrect negative relative to tall incorrect classifications
Prevalence	$\frac{FNs + TPs}{n}$	Proportion of actual positive instances in the dataset
F_1 -score	$\frac{2 \cdot precision \cdot recall}{precision + recall}$	Harmonic mean of precision and recall
F_β -score	$\frac{(1+\beta^2) \cdot precision \cdot recall}{\beta^2(precision + recall)}$	Used to account that recall is β -times as important as precision

When dealing with imbalanced or asymmetric problems, it is recommended to focus on metrics such as F_1 -score, precision, and recall [46]. Imbalanced data refers to a dataset with more instances of a particular class than others. An asymmetric problem arises when a false negative is more serious than a false positive, or vice versa. For example, consider the diagnosis of a rare disease. In both situations, training an algorithm with accuracy or misclassification rate would lead to disastrous results [21]. As mentioned in Table 3.9, F_1 -score is the harmonic mean of the precision and recall curve, which means it is a metric that represents the performance on the algorithm predicting the minority class in a single metric [21]. Another way to merge these two metrics is through the precision-recall curve (PRC), which is used to optimize the threshold of a classifier [46]. Figure 3.6 shows how to interpret these curves.

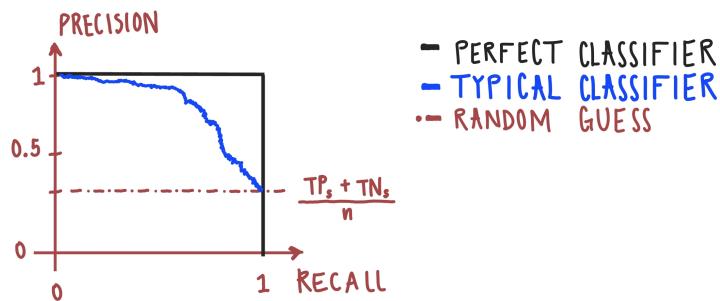


Figure 3.6: Drawing of a precision-recall curve (PRC) for three classifiers, as the threshold of the classifier decreases. The closer the area under the curve is to one, the better the classifier.

After having decided on the metric, now it is time to revise different classifiers and decide which one is worth our attention. For a quick comparison, I have decided to consider

- (i) a linear parametric model: logistic regression,
- (ii) a non-linear probabilistic model: Gaussian process,
- (iii) a non-parametric ensemble: random forest.

These three algorithms share the property of not requiring a large amount of data to perform well, but there are significant differences between each of them. Algorithm (i) differs from (ii) and (iii) by modelling the output as a linear combination of weighted inputs. Both (ii) and (iii) can handle linear and non-linear combinations of the inputs. The main difference between (ii) and (iii) is that (ii) is a probabilistic model that assumes the observations are drawn from a multivariate normal distribution, whereas (iii) makes no strong assumptions⁵ about the data and makes decisions based on information gain [21].

One can quickly implement these algorithms using scikit-learn⁶, a Python library designed to execute various machine learning algorithms [48]. For a quick comparison, I have implemented these three models using the default settings of scikit-learn⁷ and all variables of interest with one-hot encoding applied to categorical data and scaling numerical values. results of their PRC are shown in Figure 3.7 when considering `small_ds` and Figure 3.8 when considering `big_ds`.

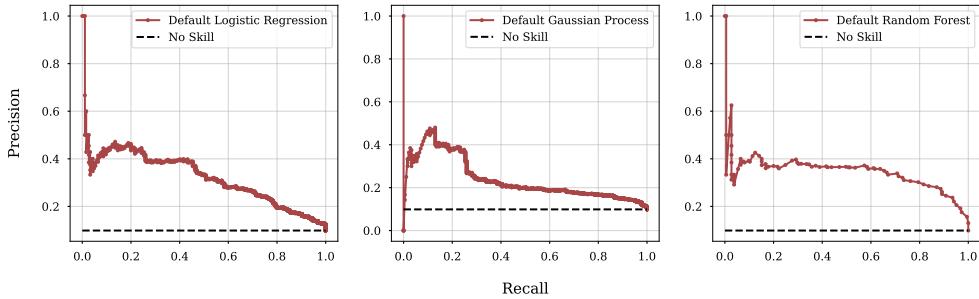


Figure 3.7: PRCs of all variables of interest and default settings in scikit-learn for logistic regression, Gaussian process and random forest; utilizing `small_ds` to label observations. A model with no skill is shown with dashed lines, which means it is a model that classifies based on random guesses. In order, the F_1 -score obtained per model were: 0.16, 0.31, and 0.26.

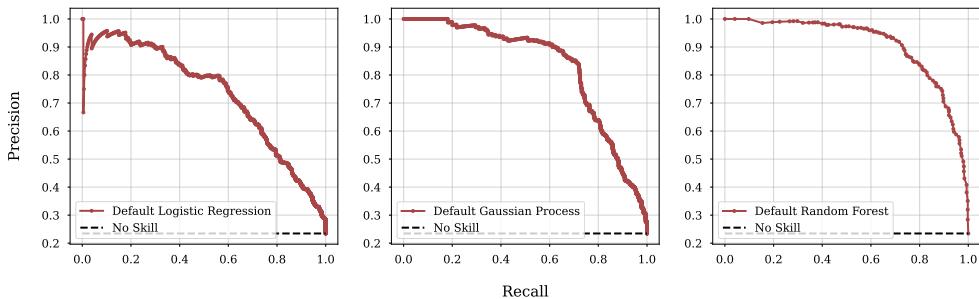


Figure 3.8: PRCs of all variables of interest and default settings in scikit-learn for logistic regression, Gaussian process and random forest; utilizing `big_ds` to label observations. A model with no skill is shown with dashed lines, which means it is a model that classifies based on random guesses. In order, the F_1 -score obtained per model were: 0.66, 0.77, and 0.81.

It is possible to see that the worst performance is on the linear classifier, regardless of the type of dataset being used. On the other hand, Gaussian process and random forest perform appropriately for `big_ds`, only; this means that `small_ds` is a case of severely imbalanced data and might require an algorithm that

⁵In general, all machine learning algorithms assume that the input data is independent and identically distributed, this is known as the i.i.d. assumption.

⁶This library uses CPU power, a library that implements GPU with Nvidia graphic cards is cuML [47].

⁷Version 1.2.2

specializes in this type of situation, like the one-class classifier [46]. For now, I will focus on the analysis of `big_ds` using Gaussian process (GP) and random forest (RF).

3.2.2 Gaussian Process and Random Forest

GP and RF are two machine learning algorithms that can be used both for regression and classification. The main difference between these two methods is that one uses a stochastic approach, while the other uses information gain of various models for making decisions [21]. I will explain in more detail the difference between them.

Gaussian Process

A collection of finite random variables whose joint distribution is a Gaussian distribution can be considered a Gaussian process. In other words, it is a method for modelling data using multivariate Gaussian distributions [49]. Figure 3.9 shows the case of a multivariate Gaussian distribution for two features contained in an arbitrary vector \vec{r} , with mean $\vec{\mu}$ and covariance matrix $\hat{\Sigma}$.

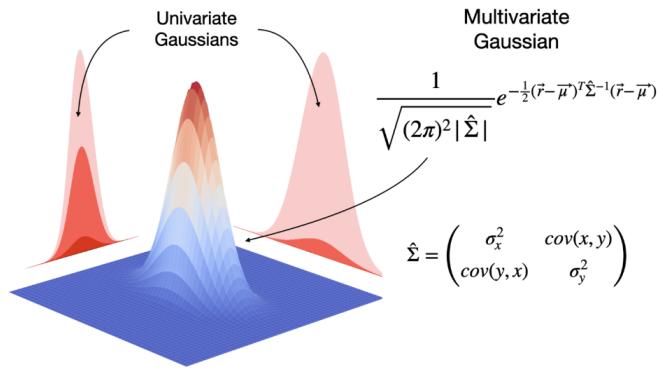


Figure 3.9: . Illustration of a bivariate Gaussian distribution. Image from: [50].

GP is a collection of random variables representing the value of a real process $f(\mathbf{x})$, at location \mathbf{x} , which is fully defined by its mean function $m(\mathbf{x})$ and covariance function $k(\mathbf{x}, \mathbf{x}')$, expressed as [21], [51]

$$f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')), \quad (3.7)$$

where

$$\begin{aligned} m(\mathbf{x}) &= \mathbb{E}[f(\mathbf{x})] \\ k(\mathbf{x}, \mathbf{x}') &= \mathbb{E}[(f(\mathbf{x}) - m(\mathbf{x})) \cdot (f(\mathbf{x}') - m(\mathbf{x}'))] = \text{Cov}[f(\mathbf{x}), f(\mathbf{x}')], \end{aligned} \quad (3.8)$$

with \mathbf{x}' denoting a different observation. It is common to set the mean $m(\mathbf{x})$ to zero, as it is possible to add an extra term in the covariance function to represent its uncertainty [52], and to treat the covariance function as kernels [21]. The heart of GPs lies in the kernel and not in $f(x)$ per se. The latter is more of a tool that allows deriving the path for inference. In fact, the problem of learning GPs is the problem of learning the optimal properties of the kernel. This is because the kernel states the relationship of given data to new data [51], [52].

Formally speaking, a kernel is a positive-definite function of two inputs \mathbf{x}, \mathbf{x}' that are Euclidean vectors; but, they could also represent categorical inputs, graphs, images, or text. Another way to interpret a kernel is by treating them as mathematical objects specifying the similarity of a function evaluated on different objects, as shown in Eq. (3.8) [52]. By adding or multiplying kernels with different characteristics, it is possible to create a new kernel that encompasses all of these properties, examples of this are shown in Figure 3.10.

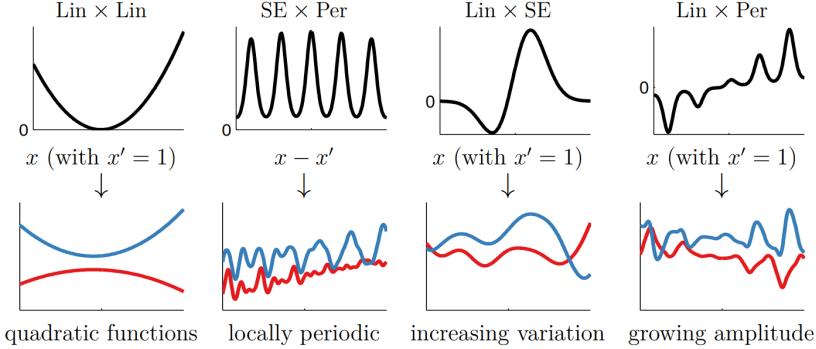


Figure 3.10: Some of the most common kernels, linear (Lin), squared exponential (SE), and periodic (Per); combined to form a new kernel. The top row of plots represents $k(\mathbf{x}, \mathbf{x}')$ and the bottom plots are two samples of a GP with the specified kernels above; this type of sampling is known as sampling the *prior* [49].

Image from: Fig. 2.2 in [52].

Once the mean and the covariance function have been specified, one proceeds to compute the predictive distribution $p(\mathbf{y}' | \mathbf{x}', \mathbf{X}, \mathbf{y})$ for the unknown target variable \mathbf{y}' , given the new input \mathbf{x}' and the data used to train the algorithm \mathbf{X} , with their corresponding labels \mathbf{y} ; namely,

$$p(\mathbf{y}' | \mathbf{x}', \mathbf{X}, \mathbf{y}) = \mathcal{N}(\mathbf{y}' | \mu_*, \Sigma_*), \quad (3.9)$$

which represents the posterior after observing the data and turns to be a GP too. Here,

$$\begin{aligned} \mu_* &= \mathbf{k}_* K^{-1} \mathbf{y} \\ \Sigma_* &= k(\mathbf{x}', \mathbf{x}') - \mathbf{k}_* K^{-1} \mathbf{k}_*^T, \end{aligned} \quad (3.10)$$

where $K_{ij} = k(\mathbf{x}'_i, \mathbf{x}'_j)$ is the covariance matrix, and \mathbf{k}_* is the row-vector $\mathbf{k}_* = (k(\mathbf{x}_1, \mathbf{x}') \dots k(\mathbf{x}_n, \mathbf{x}'))$. Then, one finds the optimal hyperparameters of the kernel by maximizing the marginal likelihood $p(\mathbf{y} | \mathbf{X})$, also Gaussian, through an optimization algorithm, like gradient descent. Broadly speaking, this is the general procedure to implement GPs for regression; an algorithm with a complexity $\mathcal{O}(n^3)$ [49]. Nevertheless, when working GPs for classification, not everything is analytically tractable since the labels are discrete and cannot have a Gaussian likelihood. In this situation, one "squashes" the output of a regression model into a class probability through what is known as a response function; for instance,

$$p(y = 1 | \mathbf{x}) = \sigma(y f(\mathbf{x})), \text{ and, } p(y = 0 | \mathbf{x}) = 1 - \sigma(y f(\mathbf{x})), \quad (3.11)$$

where $f \sim \mathcal{GP}(0, k(\mathbf{x}, \mathbf{x}'))$ and $\sigma(z)$ can be the sigmoid function $\sigma(z) = [1 + \exp(-z)]^{-1}$ or the cumulative density function of a standard normal distribution $\sigma(z) = \Phi(z) = \int_{-\infty}^z \mathcal{N}(x|0, 1) dx$, known as the probit regression [51], [53]; this depends on the problem at hand. Here, we take the sigmoid function. After

defining the model through the link function, one can obtain the unnormalised posterior as Eq. (15.33) in [53]:

$$\ell(f) = \log p(y | f) + \log p(f | X) = \log p(y | f) - \frac{1}{2} f^T K^{-1} f - \frac{1}{2} \log |K| - \frac{n}{2} \log 2\pi, \quad (3.12)$$

which can be normalised and analytically approximated by Laplace approximation [51], [53], [54]. One then gets the posterior predictive distribution as Eq. (15.48) in [53],

$$p(f_* | \mathbf{x}_*, \mathbf{X}, \mathbf{y}) = \mathcal{N}(\mathbb{E}[f_*], \text{Var}[f_*]),$$

where \mathbf{x}_* is the best point used for f ; and $f_* = f(\mathbf{x}_*)$. Then, the hyperparameters of the kernel are estimated with a gradient-based optimization algorithm, such that the marginal likelihood is maximized [54]; namely, Eq. (15.51) in [53],

$$\log p(y | \mathbf{X}) \approx \log p(y | \hat{f}) - \frac{1}{2} \hat{f}^T K^{-1} \hat{f} - \frac{1}{2} \log |K| - \frac{1}{2} \log |K^{-1} - \nabla \nabla \log p(y | f)|, \quad (3.13)$$

where \hat{f} is the maximum a posteriori estimation algorithm⁸ (MAP) applied to f . These steps are applied to obtain the GP classifier method, shown in Algorithm 3; where $k_{**} = k(\mathbf{x}_*, \mathbf{x}_*)$, \mathbf{I}_n is the $n \times n$ identity matrix, and Cholesky refers to the Cholesky decomposition, used to efficiently inverse matrices [51], [53].

Algorithm 3 Gaussian Process Classifier, based in Algorithm 15.2 in [53]. The algorithm I have implemented is *GaussianProcessClassifier()* of scikit-learn [56], which also follows this structure.

Require: MAP using iteratively reweighted least squares.

```

 $f \leftarrow 0$ 
repeat
   $W \leftarrow -\nabla \nabla \log p(y | f)$ 
   $B \leftarrow \mathbf{I}_n + W^{1/2} K W^{1/2}$ 
   $L \leftarrow \text{Cholesky}(B)$ 
   $b \leftarrow Wf + \nabla \log p(y | f)$ 
   $a \leftarrow b - W^{1/2} L^T \backslash (L \backslash (W^{1/2} Kb))$ 
   $f \leftarrow Ka$ 
until convergence
 $\log p(y | X) \leftarrow \log p(y | f) - \frac{1}{2} a^T - \sum_i \log L_{ii}$ 
% Perform prediction
 $\mathbb{E}[f_*] \leftarrow \mathbf{k}_*^T \nabla \log p(y | f)$ 
 $v \leftarrow L \backslash (W^{1/2} \mathbf{k}_*)$ 
 $\text{Var}[f_*] \leftarrow k_{**} - v^T v$ 
 $p(y_* = 1) \leftarrow \int \sigma(z) \mathcal{N}(z | \mathbb{E}[f_*], \text{Var}[f_*]) dz = 0$ 

```

The algorithm takes $\mathcal{O}(n^3)$ for fitting, and $\mathcal{O}(n^2 n')$ for prediction, where n' is the total number of new observations to be classified [53]. Extensive details on the derivation of this algorithm are found on pp. 525-528 [53], and pp. 33-48 [51].

Random Forest

Ensemble learning is a method that involves constructing a new model by combining multiple basic models, each trained in slightly different ways. By doing so, the ensemble leverages the different outputs

⁸A probabilistic framework to estimate probability densities. A good description of MAP is found in [55].

provided by the models to define the input-output relationship. [21]. RF is an instance of ensemble learning by using decision trees with different randomized samples.

A decision tree is a rule-based model that structures a graph referred to as a tree. Various disjoint regions are created to divide the input space, with each region having a fixed value to predict the output [21]. A simple tree for a classification problem is shown in Figure 3.11 using two numerical features.

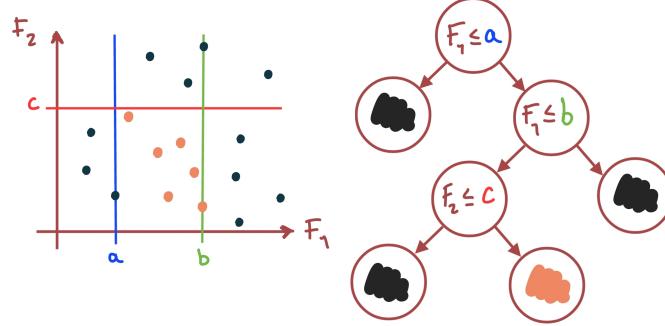


Figure 3.11: Simple drawing illustrating a plot for two numerical features and their corresponding binary decision tree. Here, a , b , and c represent real numbers creating decision boundaries, shown as lines in the plot. The top node of a tree is called the *root node*, and its subsequent branches are referred to as child-internal nodes. Nodes with a condition are known as *parent nodes*, while the nodes that follow them are their *child nodes*. A node that does not have any further branches is called a *leaf node*, which leads to a classification outcome [21].

Drawing is inspired by [57].

It is possible that observations may overlap with the decision boundary, as shown in Figure 3.11 for b ; in such situations, it can be assigned to the majority class in its vicinity, which corresponds to regions with a higher risk of misclassification. Furthermore, it is worth mentioning that if the number of leaf nodes is equal to the number of observations in the data set; then, it is said that the tree is fully grown, meaning that the model mimics the training data and it has lost its capability of generalisation, this is known as *overfitting* the model [21]. To prevent this, one can set a stopping criterion.

The challenge in decision trees lies in determining the constants that establish optimal decision boundaries for a given dataset, considering the infinite number of available options. The recommended approach for deriving these constants is by employing *greedy algorithms* [21]. Specifically, the splitting rules are generated sequentially, one at a time, starting from the root node. This process is known as the recursive binary splitting algorithm [21], which has been implemented in various versions, including CART (classification and regression trees) [58], ID3 (Iterative Dichotomiser 3) [59], and C4.5 [60].

To create a binary decision tree, for a binary classification problem, one begins by designing the root node; this implies iterating over all features and assessing which ones give the best split. There are three different criteria to measure the quality of a split through their amount of *impurity*; hence, the lower the impurity, the better [21], [61]. The different metrics are shown in Figure 3.12. Mathematically, each of the criteria for computing the impurity per node $i(N)$ is defined as [21], [61]

- misclassification error:

$$i(N) = 1 - \max(\pi_1, 1 - \pi_1), \quad (3.14)$$

- Gini index:

$$i(N) = 2\pi_1(1 - \pi_1), \quad (3.15)$$

- and, entropy:

$$i(N) = -\pi_1 \log(\pi_1) - (1 - \pi_1) \log(1 - \pi_1). \quad (3.16)$$

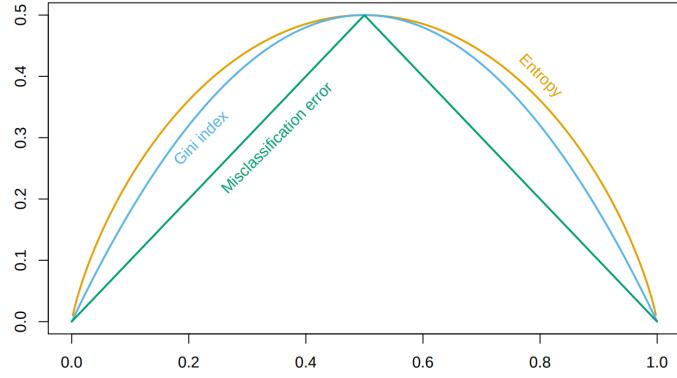


Figure 3.12: Measure of node impurity $i(N)$, vertical axis, versus the proportion of the first class π_1 in a given region denoted by a split, horizontal axis. Image from: Fig. 9.3 in [62].

Once the optimal root node has been determined, the subsequent splits are constructed based on the selected criteria and the preceding node, until the stopping criterion is met. The general idea of how to implement a binary decision tree classifier is shown in Algorithm 4.

Algorithm 4 Basic principles in a Decision Tree Classifier

Require: Stopping condition $stopping_cond$

Require: Training dataset \mathcal{D} and New observations \mathcal{D}'

Model Construction:

Split data considering all observations in \mathcal{D}

Compute quality of split according to the selected impurity metric

while $stopping_cond$ is not fulfilled and further splits are possible **do**

 Go through all possible splits considering previous ones

 Pick the split that minimizes impurity of the node

 Check for $stopping_cond$

Store tree conditions in T

Prediction:

for each row in \mathcal{D}' **do**

 Traverse tree T based on the conditions

 Get prediction for the row

One drawback of decision trees is their high sensitivity to the training data, even when the tree is not fully grown. To address this issue, an improvement can be achieved by creating multiple trees trained on the same dataset but with the introduction of randomness. These ensembles of randomised trees are known as random forests.

To create a random forest, a common practice is to start with a specified number of trees, typically ranging from 50 to 1000. The number of trees corresponds to the number of bootstrap samples, with replacement, that will be drawn from the dataset. Each subset generated through bootstrapping is then used to train an individual tree. Subsequently, a new observation can be passed through all the trees, and the final classification is determined by the majority vote across the ensemble. This process is referred to as aggregation. The overall procedure, combining bootstrapping and aggregation, is known as bagging. It is worth noting that other models can be constructed following the same reasoning by utilising different base models [21], [61].

For an ensemble to outperform a single model, two key requirements must be met: (i) each classifier within the ensemble should be uncorrelated, and (ii) the individual classifiers should have an error probability below 0.5 [61].

An additional source of randomness can be introduced to enhance the decorrelation among trees. Instead of considering different tree sizes while using all features, one can fully grow each tree but utilise different randomized subsets of features to develop them. It is worth noting that the latter requires less computational power than the former [61], but the optimal implementation depends on the dataset at hand; for instance, if there are several features with similar information, it is advisable to implement the latter technique.

Algorithm Tuning

In order for an algorithm to achieve optimal performance, it is crucial to tune its hyperparameters according to the specific dataset. The advantageous aspect of Gaussian Process is that it automatically tunes its hyperparameters while calculating the maximum likelihood [49]. Conversely, the hyperparameters of Random Forests, such as the number of trees to be created or the number of features to be considered per split, are tuned using a grid search methodology [21]. A grid search involves exploring a range of different values for the hyperparameters and evaluating the algorithm's performance for each combination. The hyperparameters that yield the best performance are then selected as the optimal choices [21], [49]. Furthermore, it is worth mentioning that, for better performance, Gaussian process benefits from scaling the numerical values previous to its implementation, while Random forests do not require said preprocessing [49], [61].

3.2.3 Feature Importance

There is a way to assess the most significant features for the algorithm to learn. The idea is based on randomly shuffling the values of a single feature and subjecting the modified dataset to the model. The performance of the model is then evaluated using a specific metric, such as precision or recall. If the model's performance significantly worsens compared to the original dataset, it is considered that the respective feature played an important role in learning [63]. It is important to note that if there are two correlated features and one of them is randomly shuffled, the model can still access their properties through the other correlated variable, thereby masking the importance of the shuffled feature [64].

Algorithm 5 Feature importance algorithm by permutation [65].

Require: Trained model $model$

Require: Training or validation dataset \mathcal{D}

$rep \leftarrow$ total amount of repetitions (here I use 200)

$m \leftarrow$ metric score based on \mathcal{D} (here I use F_1 score)

for each feature F_k in \mathcal{D} **do**

for j -th repetition in range(rep) **do**

randomly shuffle F_k to get a new dataset $\tilde{\mathcal{D}}$

$\tilde{m}_{kj} \leftarrow$ metric_score($\tilde{\mathcal{D}}$) for the j -th shuffle using the $model$

Compute importance i_k for F_k with corresponding standard deviation σ_k

$$i_k = m - \frac{1}{rep} \sum_{j=1}^{rep} \tilde{m}_{kj}, \quad \sigma_k = \sqrt{\frac{\sum_j (\tilde{m}_{kj} - \text{mean}(m_k))^2}{rep}}$$

Rank features based on greater importance.

Entropy with Low Multicollinearity Variables

Before presenting the results of the feature importance for each algorithm and subset of features, I would like to mention that I have examined the multicollinearity in the entropy variables. I found that it yielded $c(\mathbf{X}) = 45.07$. Consequently, I strategically eliminated the features with high collinearity and low importance when analysed with an RF classifier. The resulting set of features demonstrates low multicollinear-

ity and high importance. These features include WFFORM, RHOSTAR, DWDIA, BETASTAR, POHM, NEL, NUSTAR, and PLTH. Collectively, they exhibit a multicollinearity value of $c(\mathbf{X}) = 7.36$. Henceforth, this subset of features will be referred to as the *entropy with low multicollinearity*. It is worth mentioning that the research variables have $c(\mathbf{X}) = 6.97$.

3.3 Results

Up to this point, there are two algorithms, Gaussian process and random forest, that can be used to assess three different subsets of variables: research, entropy with low multicollinearity, and low multicollinearity. Consequently, we have a total of six different models to examine the variables that may provide insights into the reduction of α_R in STDB5. Additionally, I have added the categorical features to the entropy with low multicollinearity and research features for a more complete analysis. Figure 3.13 depicts the PRCs for the three cases utilizing Gaussian Process, while Figure 3.14 illustrates the PRCs for tuned Random Forests.

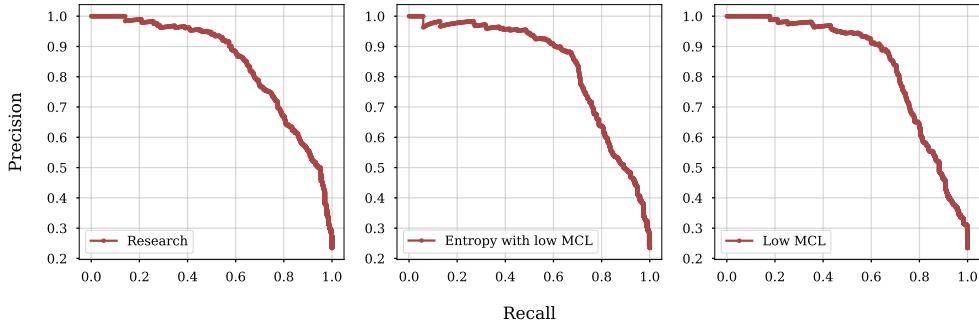


Figure 3.13: PRCs for GP classifiers with three different subsets of features being used. In order, the F_1 -score obtained per model were: 0.74, 0.76, and 0.77.

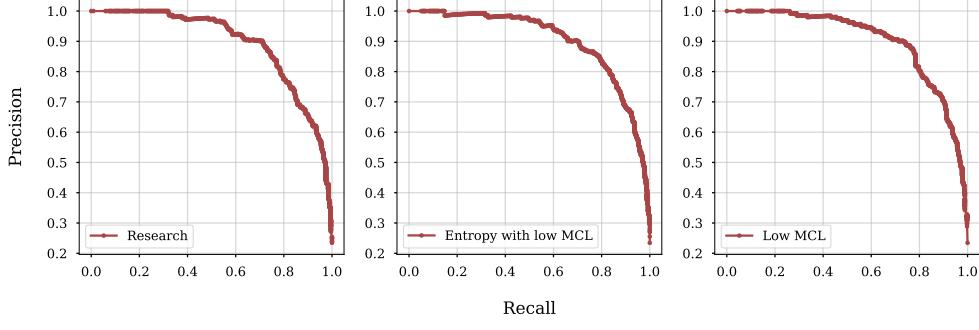


Figure 3.14: PRCs for RF classifiers with three different subsets of features being used. In order, the F_1 -score obtained per model were: 0.79, 0.81, and 0.82.

It is evident that RF consistently outperforms GP in all scenarios. Nevertheless, all algorithms effectively learned from the various datasets to make predictions that reduce α_R , exhibiting acceptable performance. The Random Forest model utilizing the subset of variables with low multicollinearity proved to be the most effective. Figure 3.15 displays the resulting first five feature importance for GP, while Figure 3.16 illustrates the feature importance for RF, across the three subsets of variables. All analyses were made with 200 rounds of shuffling.

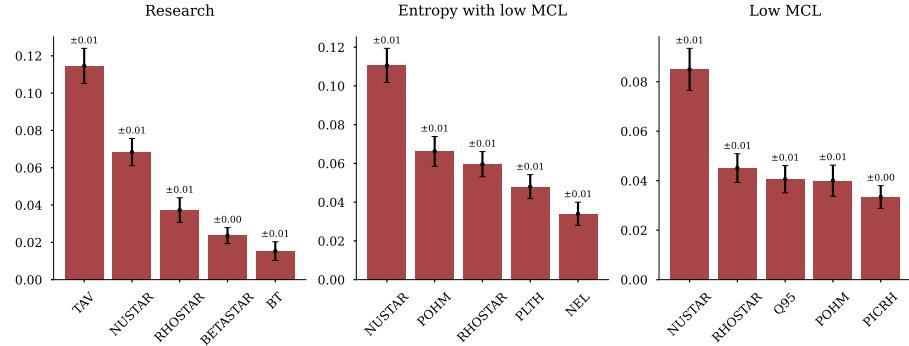


Figure 3.15: GP's most important features with standard deviations.

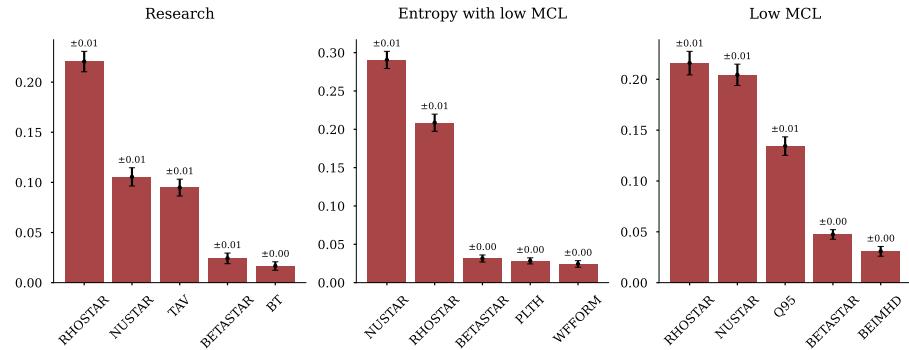


Figure 3.16: RF's most important features with standard deviations.

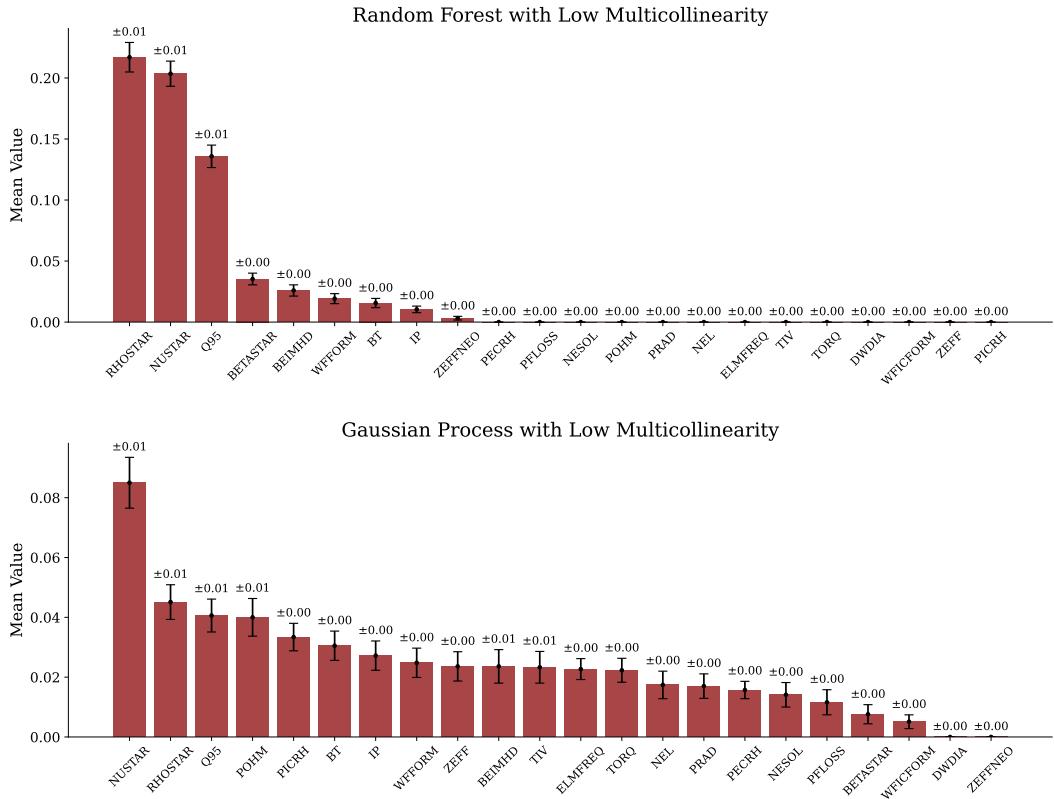


Figure 3.17: Complete feature importance for the best subset of features, for GP (bottom) and RF (top).

According to all algorithms, the normalised collision frequency and the normalised ion gyroradius emerge

as crucial factors in predicting observations that lead to a decrease in α_R . The normalised plasma beta ranks as the third most significant feature. The subsequent important features include the average temperature, safety factor, toroidal magnetic field, and others, which may vary. It is noteworthy that none of the categorical features played a significant role in the learning process of the algorithms. Figure 3.17 show the complete feature performance for the low multicollinearity variables.

It is interesting to note that GP makes use of most of the features to make predictions, while RF takes less than half of the subset to outperform GP. In the subsequent chapter, these variables will be thoroughly examined and interpreted to identify commonalities and establish connections with tokamak physics.

3.3.1 Predictions

It is convenient that the RF performs well with ρ_* , ν_* , q_{95} , and β_t since these are parameters that are relatively easy to find in other devices. If the model is reduced to these features, the performance of the RF does not decrease drastically. When only these variables are kept, the precision and F_1 -score are 0.8, with a recall of 0.79. Table 3.10 shows the main values for ITER and SPARC (a compact tokamak being developed by the MIT Plasma Science & Fusion Center [66]).

Table 3.10: Values of main features for two new toroidal machines. Values provided by the research group, except for SPARC's q_{95} , that was retrieved from [67].

	I_P	B_t	\bar{n}_e	$P_{l,th}$	R_{geo}	κ_a	ϵ	M_{eff}	ρ_*	β_t	ν_*	q_{95}	$\tau_{E,th}$
ITER	15	5.3	1.03	87	6.2	1.8	0.32	2.5	0.002	2.24	0.014	3	3.5
SPARC	8.7	12.2	3.1	25	1.85	1.97	0.31	2.5	0.003	1.20	0.03	3.2	0.77

When their respective ρ_* , ν_* , q_{95} , and β_t are put into the RF, both predictions result as **unaffected**. This could be interpreted as the machines being better described by the unaffected scaling law, presented in Table 2.2; namely,

$$\tau_{E,2.16} = 0.06 \cdot I_p^{0.78} \cdot B_t^{0.24} \cdot \bar{n}_e^{0.41} \cdot P_{l,th}^{-0.75} \cdot R_{geo}^{2.16} \cdot \kappa_a^{0.5} \cdot \epsilon^{0.79} \cdot M_{eff}^{0.22}. \quad (3.17)$$

3.4 Other Applications in Fusion

Before delving into the tokamak analyses relative to the most important features, it is worth mentioning some of the various novel applications of machine learning in fusion and nuclear technology. This section is inspired by a lecture presented by Dr. Cristina Rea⁹ at the Joint ICTP-IAEA School on AI for Nuclear, Plasma and Fusion Science [68].

Another application of multi-machine analysis is in disruption prediction. Disruptions are current-driven instabilities that abruptly terminate plasma confinement and can cause significant damage to the machine, making their avoidance crucial [69]. Random forests [70] and Deep-learning algorithms¹⁰ can be employed to develop disruption prediction algorithms, even with limited data, and transfer knowledge from existing devices to new ones [71]. These algorithms can be deployed in real-time environments to safeguard the machine [72], [73]. Additionally, the learning can be adapted to various operational regimes

⁹The current group leader in Disruption Studies at MIT Plasma Science & Fusion Center.

¹⁰A good introduction to deep-learning is found in [71].

[74]. The authors in [72] also demonstrate that time-sequence non-disruptive data is specific to the machine, while time-sequence disruption data contain device-independent knowledge.

The edge plasma conditions have a significant impact on the operation and performance of a device. The advancement of this field has relied on the use of gyrokinetic codes and fluid simulations. However, some of these codes are still in the developmental stage and others lack crucial physics. Despite various equation adaptations to account for effects such as blob dynamics or heat fluxes affecting plasma-facing components, no global code exists that fully aligns with observations [75]. The authors in [75] have demonstrated the feasibility of constraining a physics-informed deep-learning framework with partial differential equations to effectively learn and diagnose unknown turbulent fields. The resulting learning exhibits consistency with the Braginskii two-fluid theory and provides an advanced means of designing diagnostics for magnetized-turbulent plasmas. In essence, they successfully employed deep learning to unveil the dynamics of unknown turbulent plasmas based on partial observations. Physics-informed algorithms are also employed in stellarators. In W7-X, neural networks are utilized to solve the heat equation and calculate the heat flux on its divertor tiles [68]. However, one of the current limitations of physics-informed learning algorithms is that they necessitate more robust algorithms and computational frameworks due to their involvement in highly non-convex optimization problems [68].

Gaussian Process and nonlinear gyrokinetic simulations are employed to obtain a simultaneous evolution of energy sources, enabling the prediction of steady-state solutions for electron temperature, ion temperature, and electron density channels in SPARC [76]. This approach facilitates a reduction in computational costs and avoids the need for common simplifications, such as neglecting magnetic fluctuations or assuming a fixed density profile [76].

Overall, it is evident that data-driven machine learning methods are powerful tools that can address significant challenges in nuclear engineering and numerous other fields, including robotics, industrial processes, and medical research, leading to transformative advancements in these domains. These methods have proven effective in bridging the gap between practical implementations and theoretical models [77]. To conclude this chapter, I want to highlight the envisioning of the essentiality of machine learning algorithms in control rooms of nuclear devices. This concept is depicted in Figure 3.18.

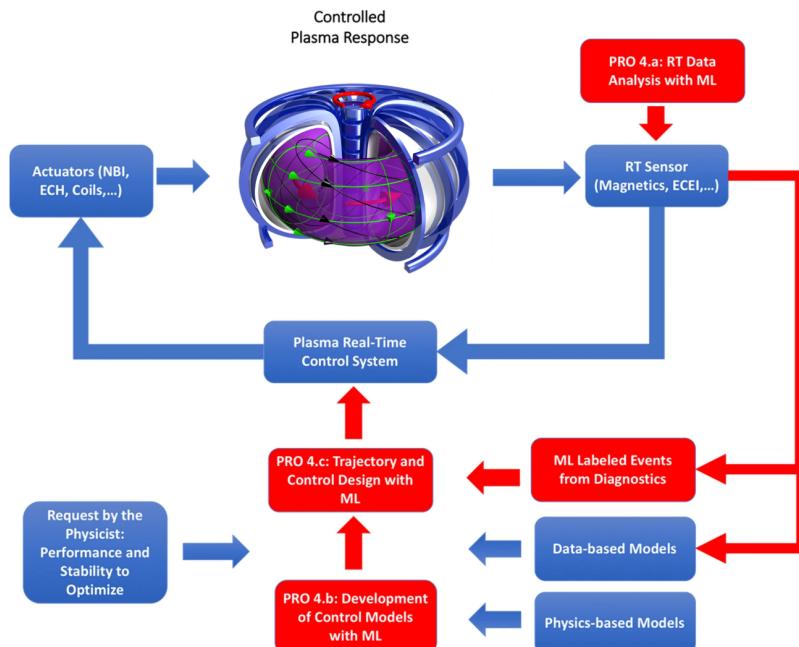


Figure 3.18: Schematic of the role played by machine learning (ML) algorithms implemented in real-time situations within control rooms. Adapted image from: Fig. 8 in [77], presented by [68].

IV

TOKAMAK ANALYSES

4.1 The Physics

In this chapter, I provide a brief overview of tokamak physics, with a specific focus on stability theory, as it directly relates to the variables of interest. Additionally, I analyze the dataset to gain valuable physical insights and present a dynamic analysis. Finally, I conclude this chapter with a concise review from an engineering perspective based on the dataset. From this point onward, the comparative plots that distinguish between the decreasing and unaffected cases will only include the new observations in STDB5, excluding any observations from DB2. This approach aims to provide a clearer comparison of the new additions in the database compared to DB2.

4.1.1 Inside a Tokamak

As briefly mentioned in the introduction, it is required to have twisted magnetic field lines¹ in order to confine the plasma effectively. Another important requirement for fusion is the existence of magnetic flux surfaces, as alpha-particles could take about 10^5 turns in a device to deliver their energy to the plasma and they can be confined within them [1]. Furthermore, the shape of the flux surface gives an indication of the density and temperature profiles. Flux surfaces are achieved through the creation of open twisted lines [1]. They also relate closely to the safety factor. For a better understanding, let us review the magnetic field configuration in a Tokamak, this is shown in Figure 4.1.

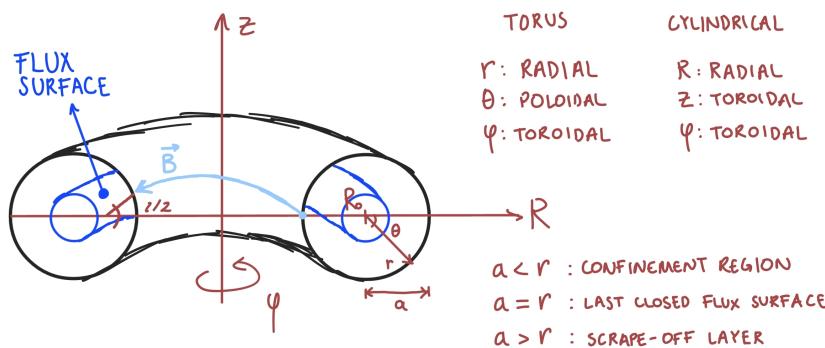


Figure 4.1: Drawing showing the two main coordinates implemented to study magnetic confinement in tokamaks and the nomenclature used in different regimes within the vacuum vessel. The rotational transform ι serves as a radial-dependent indicator of the twists in magnetic field lines. If ι is a rational number, the magnetic field lines close after n_t toroidal turns and n_p poloidal turns. Conversely, if ι is irrational, a flux surface will be covered ergodically by a single field line. Instabilities result from having a rational ι [1]. Drawing inspired in [1].

The safety factor is defined as the number of toroidal transits required for one full poloidal transit; also

¹Here, a magnetic field line is a curve that is everywhere tangential to the direction of the magnetic field.

being the inverse of the rotational transform. In a linear tokamak approximation, the safety factor is expressed as $q_s(r) = rB_\varphi/(R_{geo}B_\theta)$. The radial change of the rotational transform is known as magnetic shear,

$$s = \frac{r}{q_s(r)} \cdot \frac{dq_s(r)}{dr}, \quad (4.1)$$

which is the degree of change of the twist in the magnetic field. In general, high magnetic shear is advantageous for plasma confinement as it reduces transport losses [1]. Consequently, problems arise when the safety factor takes small values (hence the name). This is the case when the poloidal magnetic field is large due to strong gradients in the plasma current profile. These issues can lead to the occurrence of long-wavelength instabilities, such as *kink instabilities*. From stability analysis – under the assumption of circular cross-sections of the plasma – it follows that

$$\frac{n_p}{n_t} < q_s(a) = \frac{2\pi a^2}{\mu_0 R_{geo}} \cdot \frac{B_\varphi}{I_p}, \quad (4.2)$$

is a condition that must be fulfilled in order to avoid long-wave instabilities [1]. Due to the fast current ramps during the initialisation of a tokamak, this is the stage where kink instabilities are more likely to occur. Figure 4.2 shows the different kink instabilities as their poloidal turns change. Notice that the figure does not consider the case $n_p = 1$.

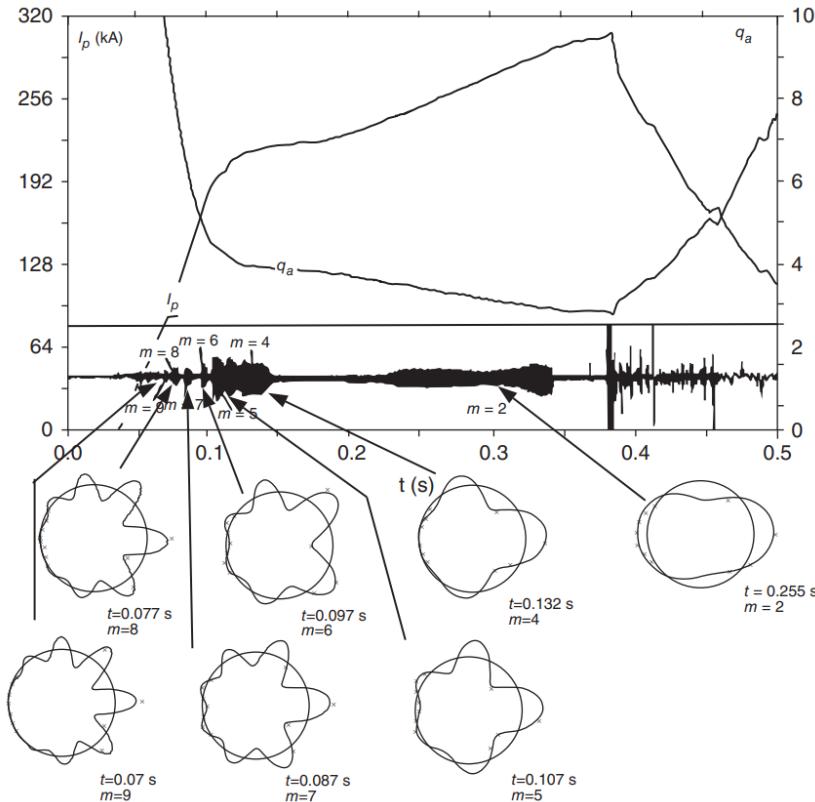


Figure 4.2: Appearance of long-wave instabilities during the current ramp up in ASDEX. Here m represents the poloidal turns. Image from: Fig. 4.4 in [78].

When $n_p = 1$, one obtains $q_s(a) > 1$ an upper limit for the toroidal plasma current, known as the Kruskal-Shafranov limit, in the form of

$$I_p < \frac{2\pi a^2 B_\phi}{\mu_0 R_{geo}} \cdot \frac{1}{2} \rightarrow [q_s(a) > 2], \quad (4.3)$$

where the $1/2$ factor was experimentally determined. When this limit is not fulfilled, it is very likely that the plasma will end up in a disruption [1]. β_t is another limited parameter in order to maintain equilibrium in fusion plasmas. Although this limit is more crucial to stellarators than to tokamaks, it is worth having a look at it.

The phenomenon known as the *Shafranov shift* occurs when the concentric flux surfaces shift outward with respect to R_{geo} [78]. This shift arises due to the creation of twisted magnetic field lines, resulting in a poloidal current called the Pfirsch–Schlüter current, which, in turn, generates a vertical magnetic field. As a result, the plasma's shape is modified [1]. The Shafranov shift increases with β_t ; as β_t increases, the plasma pressure rises, leading to an increase in the diamagnetic current. This necessitates an increase in the Pfirsch–Schlüter current in order to maintain the confinement. To avoid instabilities, the shift must be lower or equal to the minor radius [1]. Through what is known as the Grad–Shafranov Equation, it is possible to estimate a limit for β_t [78]. From this analysis, it follows that the maximum stable β , is [1]

$$\beta_{eq}(r) \approx \frac{1}{2} \frac{a}{R_{geo} q_s^2(r)} = \frac{1}{2} \epsilon q_s^{-2}(r). \quad (4.4)$$

From this, it is possible to notice that spherical tokamaks are less restrictive to this limit due to their high aspect ratio.

One final limitation I will talk about, encountered only by tokamaks, is the *Greenwald limit*, an experimentally observed soft-operational limit to the electron density that ends in disruption when surpassed [13], [79]. The explanation of this limit is focused on the mechanism that leads to strong edge cooling, or on collisionality-enhanced turbulent transport [13]. The stable parameter ranges are usually summarized in a plot known as the Hugill diagram [1]. Figure 4.3 shows a Hugill plot for JET published in 1989.

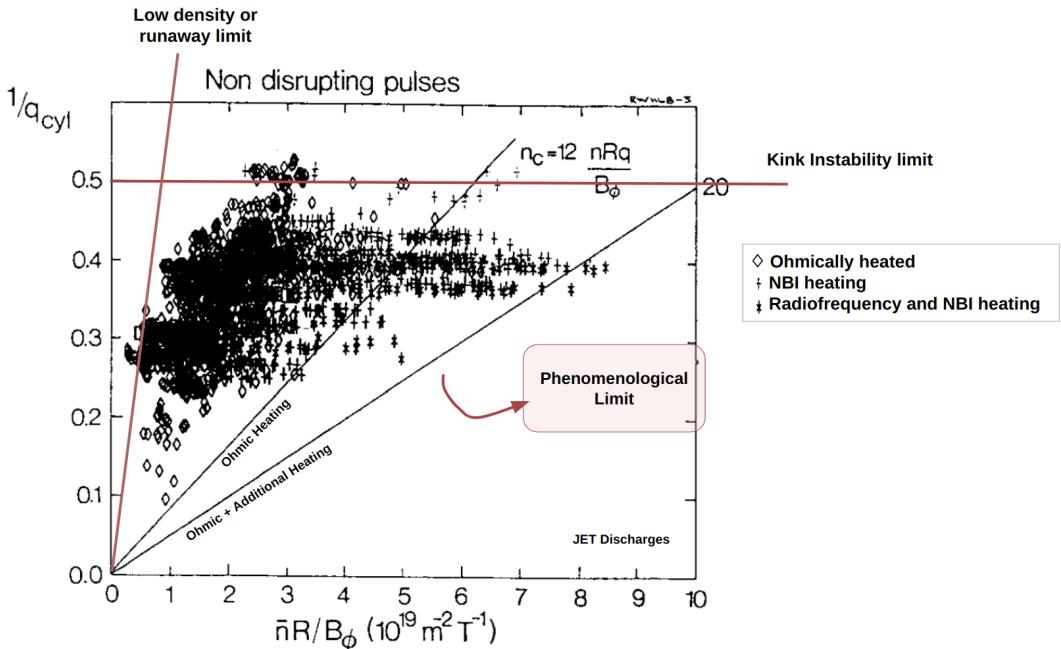


Figure 4.3: Hugill plot for old stable shots performed by JET/ Here B_ϕ is the toroidal magnetic field.
Modified image from: Fig. 4 in [80], presented in [1].

The Greenwald limit can be estimated as [13]:

$$n_{GW} = \frac{10 \cdot I_p}{\pi a^2}. \quad (4.5)$$

Nevertheless, it is worth mentioning that recently the Swiss Plasma Center at EPFL has demonstrated that ITER could use twice the amount of Hydrogen than expected without the risk of disruption [81].

4.1.2 Inside the Dataset

Figure 4.4 shows the Hugill plot for the new shots in STDB5, with respect to DB2, split into the case of decreasing and unaffected observations, based on `big_ds` labelling.

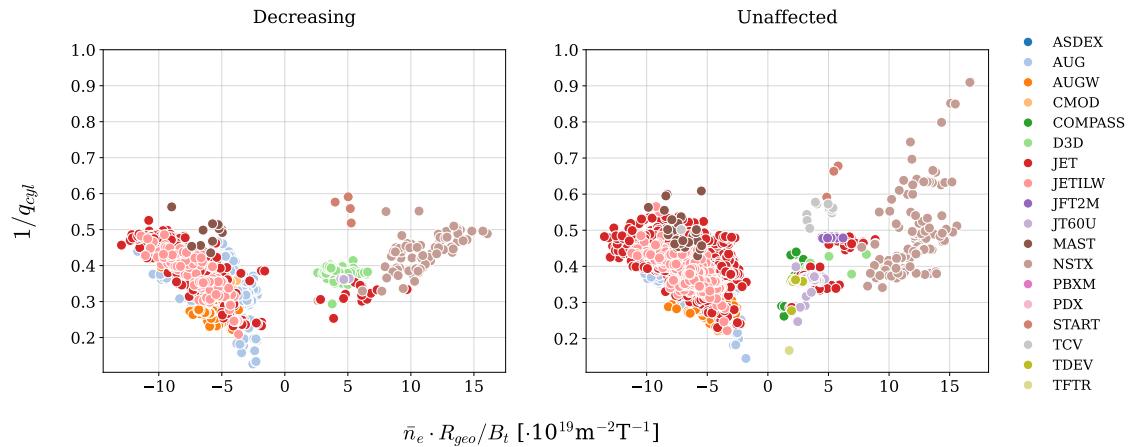


Figure 4.4: Hugill plot for the decreasing and unaffected observations based on `big_ds`. The cylindrical safety factor data was provided by the research group.

Comment

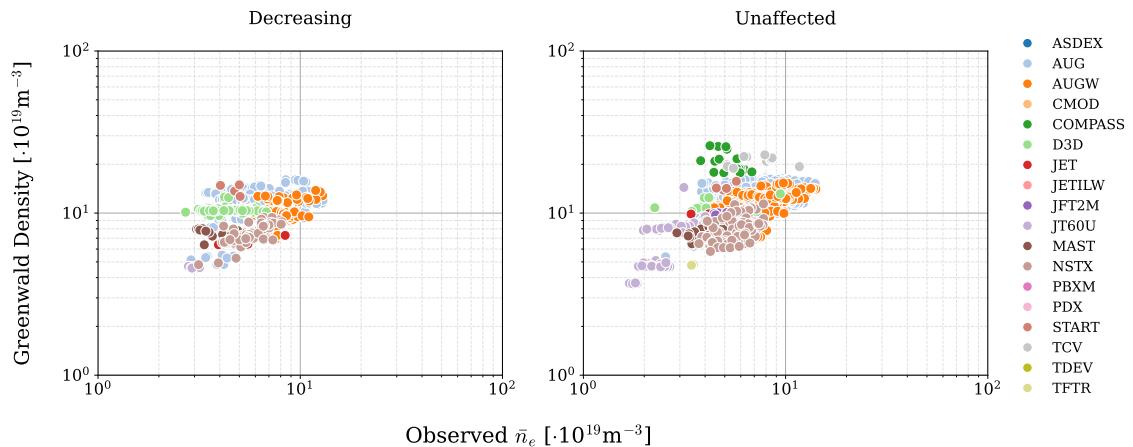


Figure 4.5: Comparison between registered density vs Greenwald density for the decreasing and unaffected observations based on `big_ds`.

Comment

It is possible to examine the tendency of the observations to adhere to the ideal MHD framework. The assumptions made within this framework include [1]:

- (i) the characteristic time length is greater than the inverse of the ion cyclotron frequency ($\tau_{E,th} >> \omega_i^{-1}$),
- (ii) the characteristic perpendicular length scale is greater than the ion gyroradius (ρ_* should be large),
- (iii) the plasma is collisional described by a Maxwellian distribution, and
- (iv) there is no dissipation, or resistivity in the plasma.

Figure 4.6 shows the comparison between the decreasing and unaffected observations, based on the labelling in `big_ds`, comparing $\tau_{E,th}$ with ω_i^{-1} . While Figure 4.7 compares between a and ρ_i .

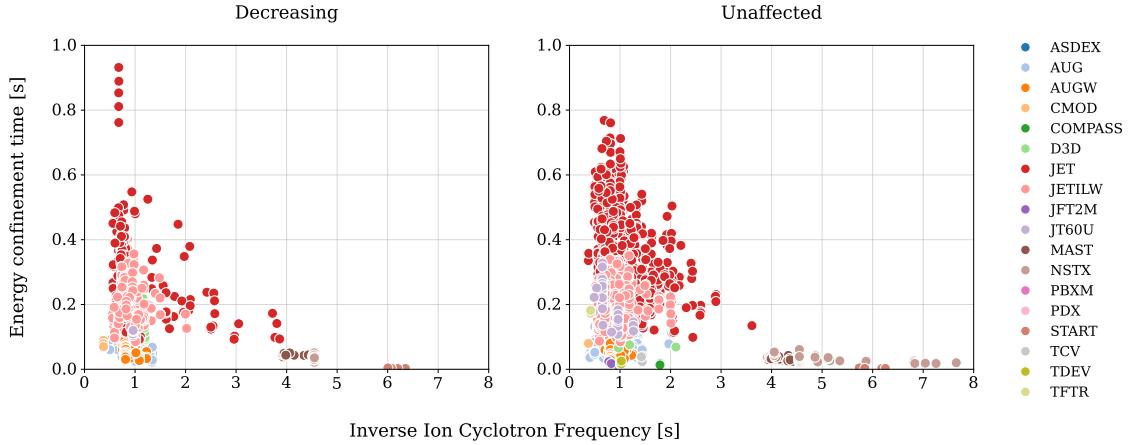


Figure 4.6: Comparison between decreasing and unaffected observations based on `big_ds`, per tokamak, to examine the first assumption of ideal MHD.

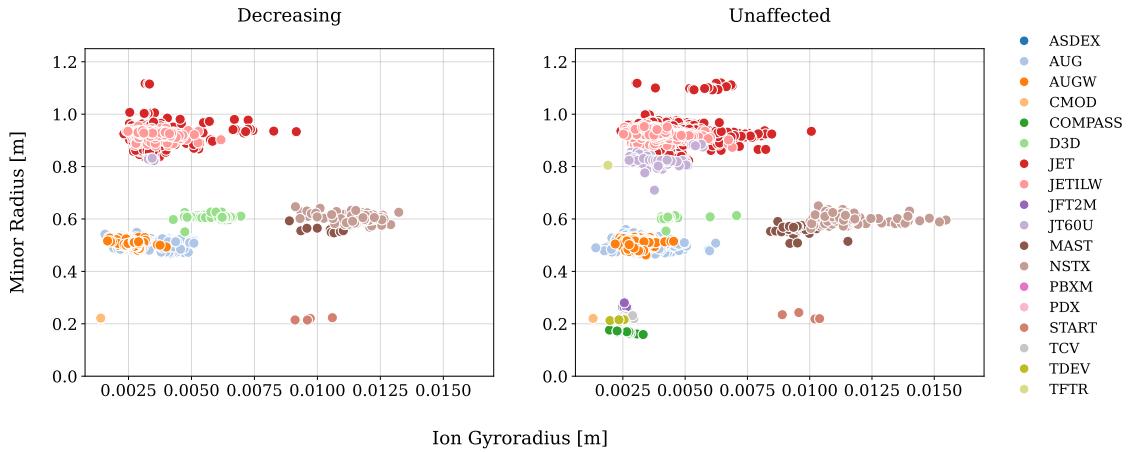


Figure 4.7: Comparison between decreasing and unaffected observations based on `big_ds`, per tokamak, to examine the second assumption of ideal MHD.

comment on these. V14-Alf

There is a way to gain some insight into the physics of a dataset through specific variables. One variable that exhibits an interesting attribute is χ_ρ , the regressor parameter of the dimensional scaling law, found in Eq. (1.5). The significance of this variable stems from the fact that Eq. (1.5) can be expressed in terms of the Bohm time $\tau_B = a^2/D_B$, where $D_B \propto \hat{T}/B_t$ denotes the Bohm diffusivity [6]. Considering that $\tau_B \propto \omega_i^{-1} \rho_*^{-2}$, the dimensionless scaling can be formulated as

$$\tau_{E,th} \propto \tau_B \cdot \rho_*^{2+\chi_\rho} \cdot \beta_t^{\chi_\beta} \cdot v_*^{\chi_v} \cdot q_{cyl}^{\chi_q} \cdot R_{geo}^{\chi_R} \cdot \kappa_a^{\chi_\kappa} \cdot \epsilon^{\chi_\epsilon} \cdot M_{eff}^{\chi_M}. \quad (4.6)$$

For the case where $\chi_\rho \sim -2$, the scaling is referred to as *Bohm scaling*, as the macroscopic plasma dimensions are more representative of the turbulence scale length than the gyroradius. For the case where $\rho_i \ll a$, so ρ_* is considerably small, one is encountering a strongly magnetized plasma [82]. When $\chi_\rho \sim -3$, the scaling is referred to as *gyro-reduced Bohm* as the gyroradius is proportional to the Bohm-normalized diffusivity, a situation expected from various turbulence theories [6]. Table 4.1 shows the value taken by χ_ρ for the different subsets presented in Table 2.2.

Table 4.1: Estimate of the regression parameter χ_ρ in Eq. (1.5) to gain a general insight on the physics per dataset.

	DB2	STDB5	$\tau_{E,0.64}$	$\tau_{E,2.16}$	$\tau_{E,0.99}$	$\tau_{E,1.71}$
χ_ρ	-3.09	-1.80	-1.31	-2.63	-1.5	-2.08

From Table 4.1, it is possible to notice that the observations that do not influence the reduction on α_R , when utilising the `small_ds`, tend to follow a gyro-reduced Bohm scaling. Whereas for the `big_ds` is somewhat between the two cases. It is interesting to observe the considerable difference between DB2 and DB5, this could be due to ...

4.2 Variables of Importance and Tokamak Characteristics

According to the previous analyses, the normalized ion collision frequency (NUSTAR), the normalized ion gyroradius (RHOSTAR), the plasma safety factor at the 95% poloidal flux surface (Q95), and the normalized plasma beta (BETASTAR) are some of the main features that one should pay attention when determining which observations influence the reduction on α_R . These are also four, out of the seven, parameters in the dimensionless form of the energy confinement time $\omega_i \tau_{E,th}$. So, let us further revise these quantities. Table 4.2 shows the descriptive statistics of these four variables and Figure 4.8 shows a 3-dimensional scatterplot for ρ_* , v_* , and β_t . Click [this link](#)² to see the rotation of the left plot.

Table 4.2: Descriptive statistics for the main variables in STDB5 split into two cases: without spherical tokamaks (left) and spherical tokamaks only (right). This is done to highlight the difference among the ranges in features like the normalized plasma beta, confinement time, and normalized ion collision frequency.

STDB5 (without with only) Spherical Tokamaks					
	TAUTH	RHOSTAR	NUSTAR	BETASTAR	Q95
mean	0.18 0.03	0.01 0.02	0.19 0.07	1.350 11.73	3.83 7.46
std	0.15 0.01	0.0 0.0	0.21 0.02	0.56 3.57	0.88 1.61
min	0.01 0.00	0.00 0.01	0.00 0.02	0.21 4.48	1.87 3.26
25%	0.08 0.03	0.00 0.02	0.06 0.06	0.90 9.06	3.21 6.26
50%	0.13 0.04	0.01 0.02	0.12 0.07	1.250 11.93	3.64 7.48
75%	0.25 0.04	0.01 0.02	0.23 0.09	1.750 14.19	4.25 8.62
max	1.32 0.06	0.02 0.05	2.89 0.13	3.520 20.68	11.13 11.31

²github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roBRN.gif

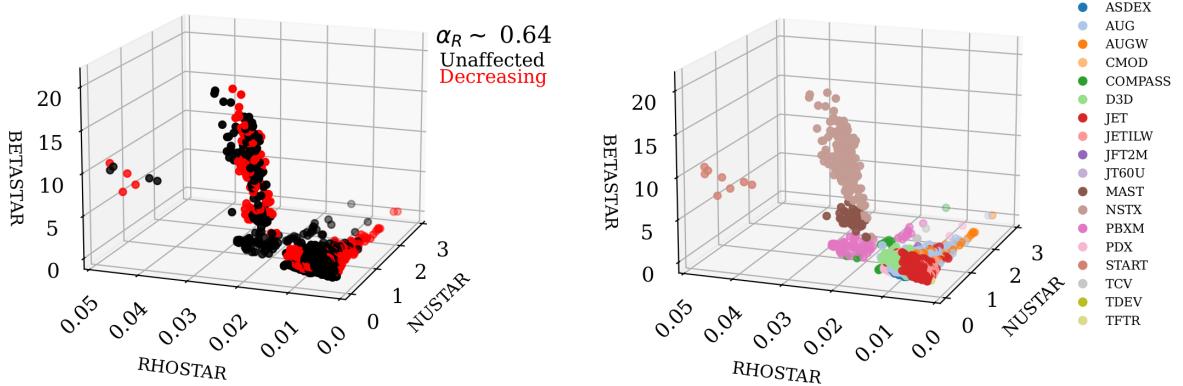


Figure 4.8: 3-dimensional scatter-plot of ρ_* , ν_* , and β_t showing the observations that influence α_R (left) and its corresponding tokamak (right).

Overall, it is evident that spherical tokamaks generally exhibit significantly higher normalized plasma beta values compared to non-spherical devices. Additionally, it is worth noting that among the devices considered, START is the only one capable of achieving $\rho_* > 0.03$. This range of observations corresponds to cases that have an impact on α_R , as well as cases that do not affect α_R . However, spherical tokamaks are not capable of achieving large ν_* values, compared to other devices like ASDEX-U, ASDEX-W, and COMPASS. But, how do these tendencies relate to the energy confinement time? Figure 4.9 shows the variation of $\tau_{E,th}$ based on these three parameters.

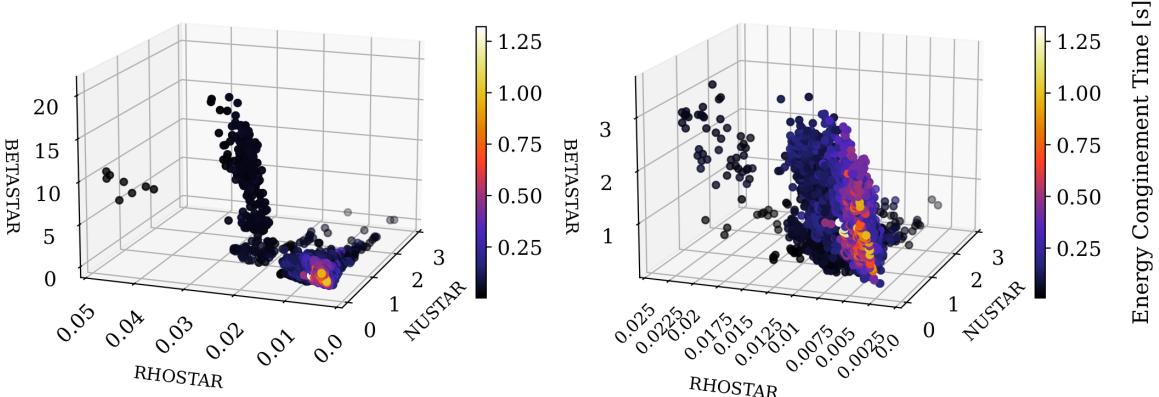


Figure 4.9: Normalized plasma beta, with normalized ion gyroradius and normalized collisionality plotted along with $\tau_{E,th}$ for the complete STDB5 (right) and the case where spherical devices has been removed (right).

It is reasonable to expect that a larger value of β_t would lead to a longer $\tau_{E,th}$. However, it is interesting to note that devices with higher β_t actually exhibit the lowest energy confinement times. However, as already discussed, several variables influence $\tau_{E,th}$, some of which can be observed experimentally, while others are theoretically estimated. Additionally, there are unknown variables, commonly referred to as latent variables. Examples of latent variables include plasma rotation and the electron-ion heating ratio [6].

Let us now investigate the three main features in the RF: ρ_* , ν_* , and q_{95} . Figure 4.10 shows the 3-dimensional plot for these variables with their labels (left³) and their respective tokamak (right).

³Click to see its rotation: github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roNRQ95.gif.

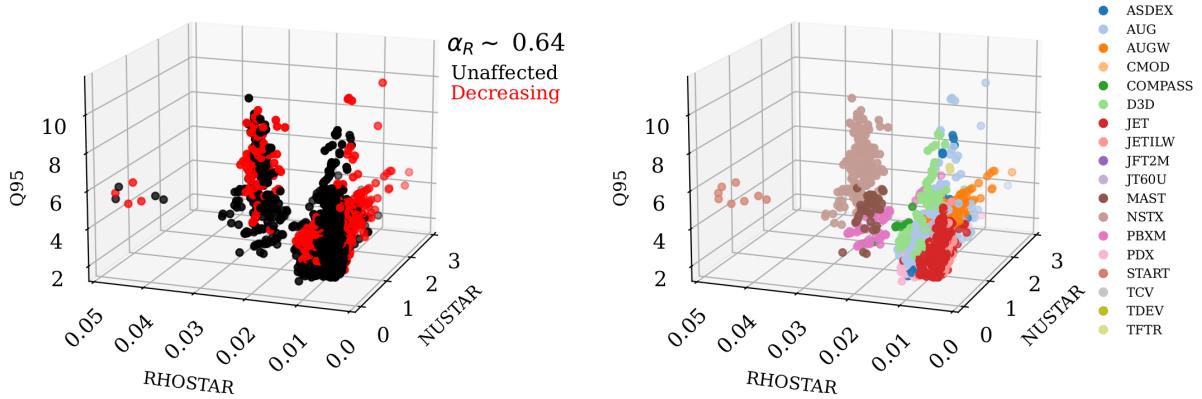


Figure 4.10: 3-dimensional scatter-plot of ρ_* , ν_* , and q_{95} showing the observations that influence α_R (left) and its corresponding tokamak (right).

In contrast to the previous case, when considering β_t instead of 9_{95} , there is no perfect separation between the spherical devices and the toroidal devices. In the vicinity of the cluster containing MAST and NSTX observations, there are toroidal shots that slightly overlap with them, belonging to PBXM and COMPASS.

For completeness, Figure 4.11 illustrates the variation of the energy confinement time given these three parameters, along with an additional azimuthal rotation in the plot.

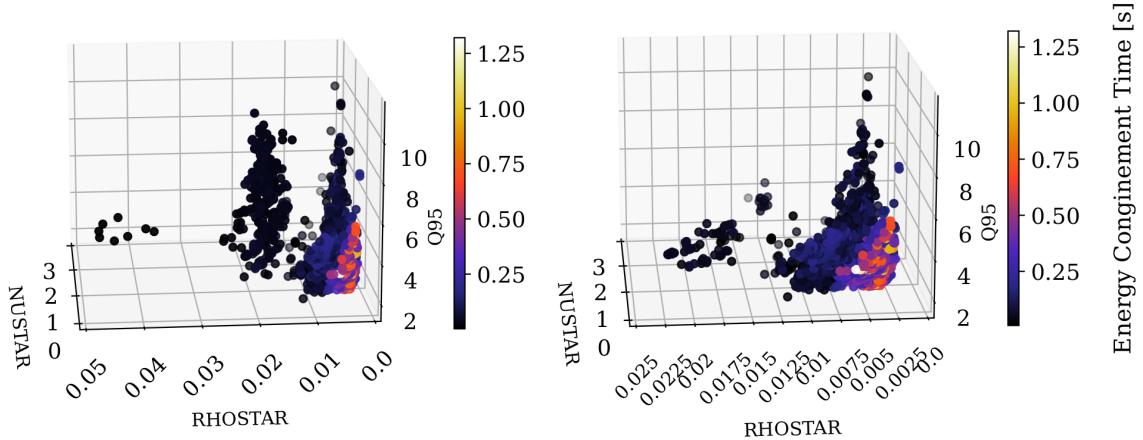


Figure 4.11: Safety factor, with normalized ion gyroradius and normalized collisionality plotted along with $\tau_{E,th}$ for the complete STDB5 (right) and the case where spherical devices have been removed (right).

4.2.1 Dynamic Analyses with Random Sampling

Now that the key features have been identified, it is possible to retrieve some of the sample subsets that influence α_R , shown in Figure 2.5 (right), and plot the change of the labelling in these variables as α_R decreases. Figure 4.12⁴ shows a comparison between the `big_ds` (left) and the `small_ds` (right) for ρ_* , ν_* , and q_{95} . By clicking [this link](#)⁵, you can see the dynamic evolution of the influence on α_R , as well as the rotation of the plot. From this, it is possible to observe that as α_R decreases, a clearer separation between the affected and unaffected observations becomes more pronounced.

⁴Click to see its rotation: github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roCoNRQ.gif

⁵github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roDynNRQ.gif

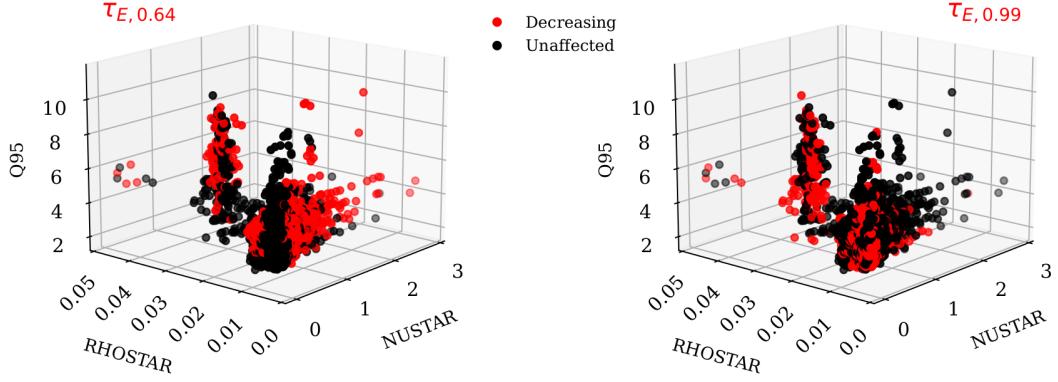


Figure 4.12: Comparison of between the observations that influence α_R based on `big_ds` (left) and the `small_ds` (right).

As shown in Table 4.2, and Figure 4.10, there is a significant difference between the spherical and toroidal devices, so let us have the same analysis by removing the spherical data. Figure 4.13⁶ shows the equivalent to Figure 4.12, but with removed spherical data. By clicking [this link](#)⁷, you can see the dynamic evolution of the influence on α_R , as well as the rotation of the plot. By having both perspectives, it is easier to descry the observations that decrease α_R in terms of ρ_* , ν_* , and q_{95} .

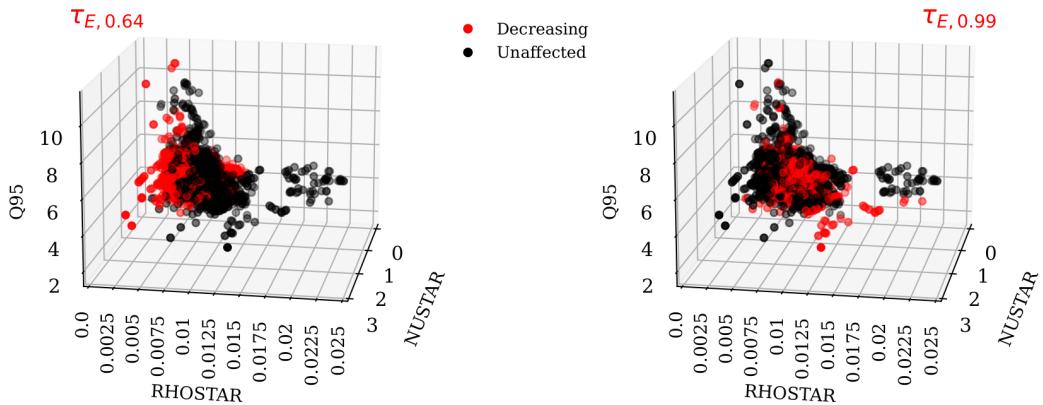


Figure 4.13: Comparison of between the observations that influence α_R based on `big_ds` (left) and the `small_ds` (right), for ρ_* , ν_* , and q_{95} . Here, observations for MAST, NSTX, and START have been removed.

Now, let us perform the same analysis, but we use β_t instead of q_{95} . Figure 4.14⁸ shows the comparison between the labels of the decrease and unaffected observations, now considering β_t . Again, the labelling based on `big_ds` gives a clearer structure to the influencing observations compared to the `small_ds`. Figure 4.15⁹ shows the same comparison, with the removal of spherical tokamaks.

⁶Click to see its rotation: github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roCoNRQ_noSPHE.gif

⁷github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roDynNRQ_noSPHE.gif

⁸Click to see its rotation: github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roCoNRB.gif, and dynamic evolution:github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roDynNRB.gif

⁹Click to see its rotation: github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roCoNRB_noSPHE.gif, and dynamic evolution:github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roDynNRB_noSPHE.gif

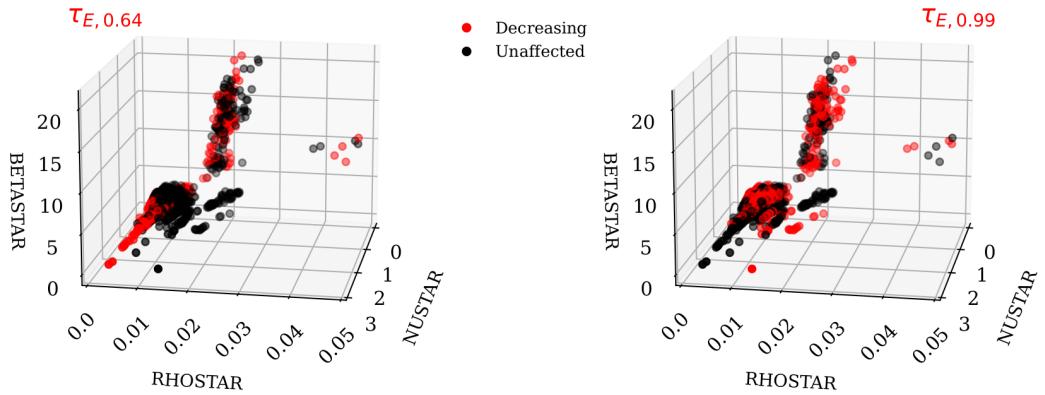


Figure 4.14: Comparison of between the observations that influence α_R based on big_ds (left) and the small_ds (right), for ρ_* , ν_* , and β_t

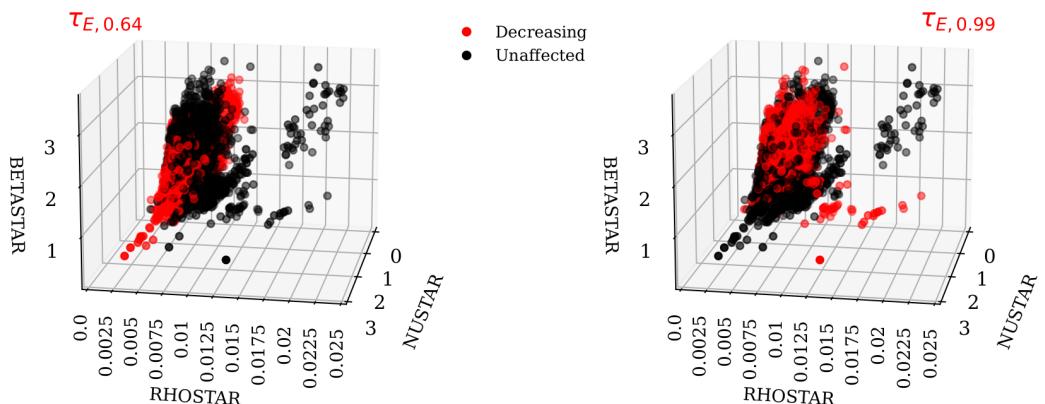


Figure 4.15: Comparison of between the observations that influence α_R based on big_ds (left) and the small_ds (right), for ρ_* , ν_* , and β_t . Here, observations for MAST, NSTX, and START have been removed.

One of the questions I asked in Chapter 2 was: "out of all the dataset subsets shown in Figure 2.5 (right), which one will provide the most informative insights into the factors causing the decrease in α_R ?". It is now evident that, for supervised learning, the dataset with the smallest α_R obtained provides more information than the smallest subset size containing a significant decrease in α_R .

There is a branch in machine learning known as *unsupervised* machine learning. This approach consists in not giving labelled data to the algorithm for it to learn. One example is the search for characteristic clusters within the data. Initially, in this project, I attempted to implement unsupervised learning before supervised learning using all the features of interest. Nevertheless, the results obtained were too complex to interpret. Now that I have gained insights into the main features, it is possible to explore characteristic clusters. In this situation, the differentiation made by the small_ds may prove more beneficial than that made by the big_ds, primarily due to the former containing fewer observations and thus less noise. However, this aspect requires further investigation.

4.3 The Engineering

In 1997, JET achieved fusion plasmas utilising graphite walls and a 1:1 mixture of deuterium and tritium. However, there has been a trend towards replacing carbon walls with metallic walls, commonly referred to as "ITER-like walls." For example, JET's ITER-like walls are composed of Beryllium and tungsten, with

the divertor entirely made of tungsten. The motivation for these replacements lies in graphite's issues with erosion and high fuel retention [83]. Although graphite has a higher damage threshold compared to Beryllium, it is not susceptible to chemical erosion and has a low atomic number, which is crucial for mitigating undesired Bremsstrahlung radiation [1], [83]. Tungsten is incorporated to improve Beryllium's damage threshold as it has a high melting point (3,422 °C) [83]. However, it also has a high atomic number, which increases Bremsstrahlung radiation and leads to substantial losses due to electron-ion collisions [1]. Overall, the design and analysis of plasma-facing components and material science constitute an active research field that continues to influence new projects.

In this section, I will present a brief analysis of the materials that characterize the decreasing and unaffected observations concerning α_R . Firstly, let us examine how each case relates to the energy confinement time and the main features found in the previous chapter.

Figure 4.16¹⁰ illustrates the wall materials in relation to the energy confinement time, safety factor, and normalized gyroradius. In both cases, the observations involving walls made of Inconel (an alloy of nickel, chromium, and iron [84]), or Inconel combined with Carbon, demonstrate higher confinement times. The devices associated with these observations include COMPASS, D3D, JET, and JETILW, with both subsets encompassing data from 1994 to 2016. The divertors of these devices are constructed using various materials. Carbon is utilized in COMPASS, D3D, and JET; with the latter combining it with Beryllium. JETILW employs only Tungsten. It is worth noting that these observations do not exhibit high safety factors compared to others, in both datasets. AUG and AUGW employ Tungsten walls, with their divertors composed of Carbon with Tungsten and Tungsten, respectively. CMOD, JFT2M, MAST, PBXM, and PDX feature stainless steel walls. ASDEX, TCV, and TDEV have walls made from a combination of carbon, while AUG, JT60U, MAST, NSTX, and TFTR have walls composed purely of carbon. Finally, the isolated observations of AL material belong to START, with its divertor made of Inconel. In these registers, the only device that contains Molybdenum in its divertor is CMOD.

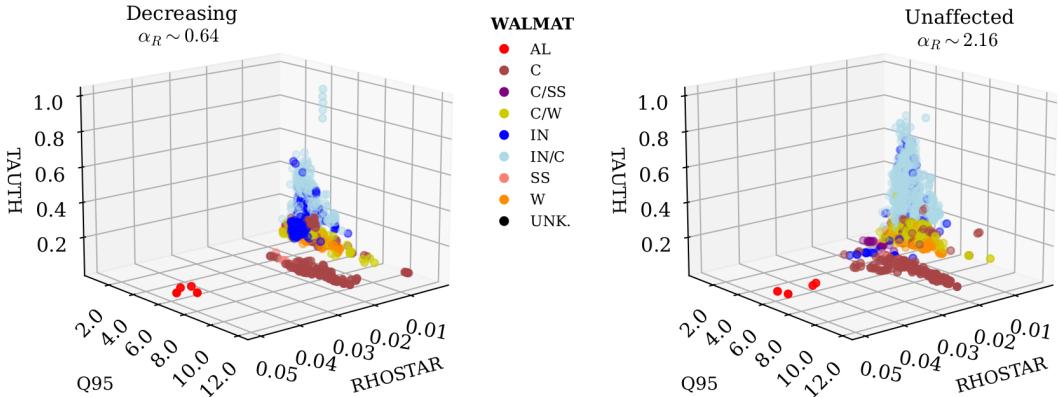


Figure 4.16: Wall material present in the decreasing (left) and unaffected (right) dataset based in big_ds for the two of the main features of interest. The labels are: AL (AL), Carbon (C), Inconel (IN), stainless steel (SS), Tungsten (W), and unknown (UNK.).

In tokamaks, limiters are strategically placed within the vacuum vessel to protect the machine against plasma. However, this concept was later replaced by the invention of divertors [1], [85]. On the other hand, JET incorporates divertors and small wall-guard limiter tiles. These tiles are individually attached to the wall, allowing for easy removal when replacement or inspection is required. Their design also proves useful for researching Tritium accumulation, which is a current concern for ITER [86]. Figure 4.17¹¹ shows the 3-dimensional plot for $\tau_{E,th}$, q_{95} , and ρ_* with their corresponding limiter material.

¹⁰Click to see its rotation: github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roWALNRT.gif

¹¹Click to see its rotation: github.com/Chinnasf/FUSION-EP-Master-Thesis/blob/main/data/GIFs/roLIMNRT.gif

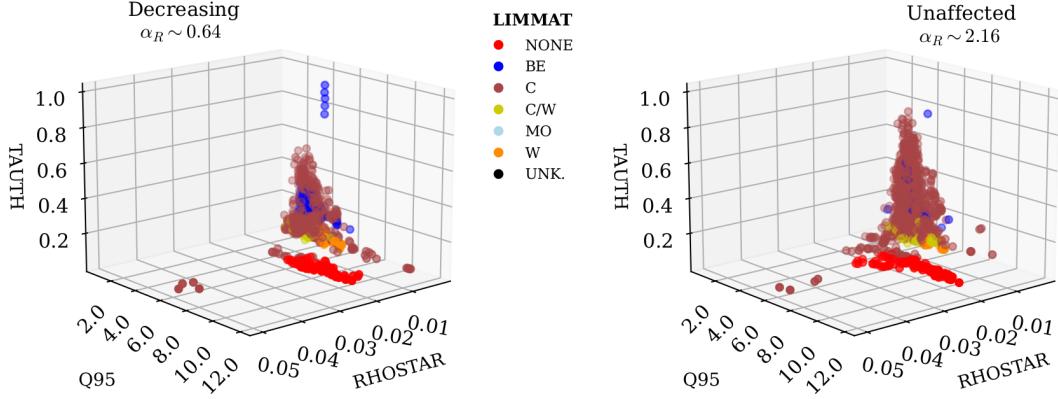


Figure 4.17: Limiter material present in the decreasing (left) and unaffected (right) dataset based in `big_ds` for the two of the main features of interest. The labels are: Beryllium (BE), Carbon (C), Molybdenum (MO), Tungsten (W), and unknown (UNK).

Figure 4.16 along with Figure 4.17 provides a better perspective on the main plasma-facing components that contribute to higher energy confinement time, with $q_{95} \sim 3$ and low ρ_* . The highest recorded energy confinement time is 0.93 s, observed in 1990 for JET in the decreasing dataset. However, the highest $\tau_{E,th}$ recorded in STDB5 is 1.32 s, also in 1990 (coming from DB2) for JET, classified as unaffected. This is depicted in Figure 4.18, where the comparison is done now between datasets.

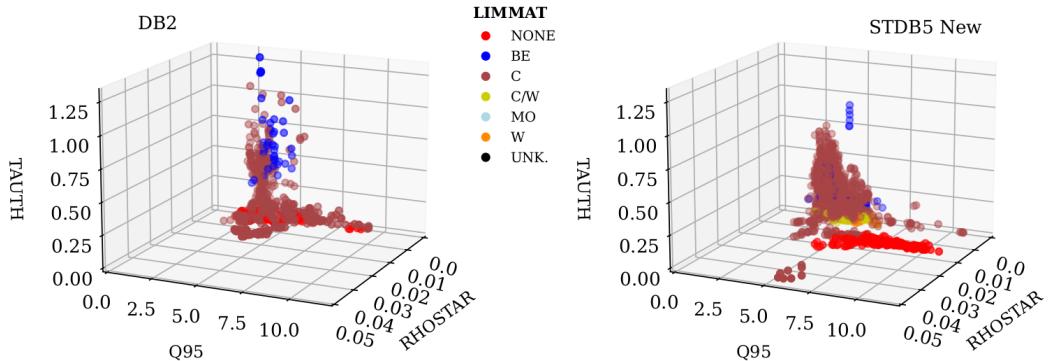


Figure 4.18: Limiter material present in the DB2 (left) and new shots, w.r.t. DB2, in STDB5 (right).

To close this section, it is worth mentioning one of the current hot topics in material science and fusion research, which is the development of limiters and *divertorlets* using Lithium and Gallium, referred to them as "liquid metals" [87]. The implementation of these materials is expected to enable the machine to withstand higher heat fluxes while simultaneously enhancing plasma performance [88].

V

CONCLUSIONS

A

DERIVATION OF RESEARCH VARIABLES

In this chapter, I will provide a step-by-step explanation of how to derive Eq. (3.5) and Eq. (3.6) to gain a deeper understanding of why the *research variables* are of particular interest. The derivation is based on an attempt to estimate the impact of the scaling law on tokamak design, using a zero-dimensional analysis. These mathematical derivations heavily draw upon the ideas and research findings presented in [13], which serves as the primary reference for this section. However, it is important to note that the content presented here is not intended to replicate or mimic the material found in [13]. Instead, the purpose of this derivation is to offer a more accessible and reader-friendly approach, especially for those without a strong background in tokamak physics. Here, the temperature and any other energy are expressed in keV. Furthermore, flat profiles of current and density are considered.

A Brief Analysis on the Design of a Tokamak

When having the target fusion power P_{fus} and fusion gain Q , for instance, $P_{fus} = 500$ MW and $Q = 10$; as well as prescribed geometric coefficients, it is possible to figure out the optimal major radius R_{geo} and toroidal magnetic field B_t for best stability. The first thing one should think about is the possible risks that might terminate the plasma confinement; as already mentioned, one of them is the Greenwald limit n_{GW} , estimated as:

$$n_{GW} = \frac{10 \cdot I_p}{\pi a^2}.$$

Now, if the length of the poloidal cross-section is defined as $L_\theta = 2\pi a \cdot \sqrt{(1 + \kappa_a^2)/2}$ it is possible to approximate the plasma current as [13]:

$$I_p = \frac{1}{\mu_0} L_\theta B_\theta, \quad (\text{A.1})$$

where B_θ is the poloidal magnetic field and can be obtained from the safety factor q_{95} . One can use these definitions, and the fact that $a = \epsilon R_{geo}$, to have an expression for the plasma current in terms of the toroidal magnetic field; namely,

$$I_p = C_I \cdot \frac{\epsilon^2}{q_{95}} \cdot B_t R_{geo}; \text{ with, } C_I = \frac{2\pi}{\mu_0} \sqrt{(1 + \kappa_a^2)/2} \cdot 10^{-6}. \quad (\text{A.2})$$

With this, it is possible to get an expression for the Greenwald Litim in terms of R_{geo} and B_t , instead of I_p and a , such that

$$n_{GW} = \frac{10}{\pi} \cdot \frac{C_I \epsilon^2 B_t R_{geo}/q_{95}}{\epsilon^2 R_{geo}^2} = \frac{10}{\pi} C_I \cdot \frac{B_t}{q_{95} R_{geo}}. \quad (\text{A.3})$$

From this, one gets the normalized density $n_N = \bar{n}_e/n_{GW}$. Thus,

$$\bar{n}_e = \frac{10}{\pi} C_I n_N \frac{B_t}{q_{95} R_{geo}}. \quad (\text{A.4})$$

Now, let's discuss MHD instabilities. This is a complex and extensive topic; but, for this section, it is sufficient to understand that these instabilities can occur due to perturbations that cause the displacement of the plasma, such as the *Rayleigh–Taylor interchange instability* or kink instabilities [89]. If the perturbation propagates perpendicular and slightly parallel to the magnetic field, the plasma will exhibit *ballooning instabilities*, which are pressure-driven instabilities that can result in the loss of plasma confinement [1], [89]. One can reduce the chance of observing MHD instabilities when the tokamak complies with the β -limit, as mentioned in Chapter 4. For this analysis, it is convenient to express this limit in the form of a percentage; namely, [13]:

$$\beta\% = 100 \cdot \beta_t \leq \beta_{eq} = g \cdot \frac{I_p}{a B_t}, \quad (\text{A.5})$$

where, and g is a proportionality constant, often considered between 2-4, due to the Troyon limit [90]. From this, the normalized plasma-beta β_N is defined,

$$\beta\% = \beta_N \cdot \frac{I_p}{a B_t} \quad (\text{A.6})$$

such that the stability limit can be read as $\beta_N < g$ [13]. Let us now define the type of species that will be in the tokamak. Figure A.1 shows the highest fusion reaction rate $\langle \sigma v \rangle$ versus the plasma temperature for different elements.

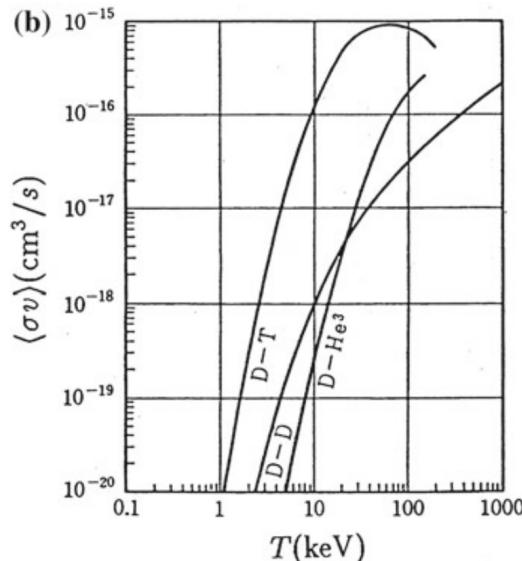
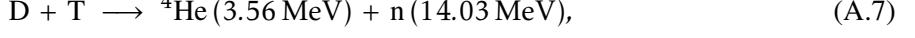


Figure A.1: Feasibility of obtaining fusion power depending on the species in the plasma at a given temperature. The lines shown are for Deuterium-Tritium (D-T), (Deuterium-Deuterium) D-D, and Deuterium-Helium-3 (D-He³). Image from: Fig. 1.2 (b) in [89].

Since D-T is more likely to undergo fusion at lower temperatures, compared to other fusion fuels, it is a popular option for nuclear fusion research. Nevertheless, Tritium is an expensive and difficult element to work with [1], which is why some companies prefer to research D-He³ [91]. ITER will be working with D-T [8]; hence, these are the species that we are considering in this study. Its fusion reaction reads



with a total energy release of $E_{DT} = 17.59 \text{ MeV}$, per fusion reaction. The ratio of the total energy transferred by the alpha particles $\lambda = 17.50/3.56 \approx 4.94$ [13]. Knowing the density of the deuterium and tritium (n_D and n_T , respectively), one can approximate the P_{fus} through Figure A.1 and

$$P_{fus} = n_D n_T \langle \sigma v \rangle_{DT} E_{DT} V_t, \quad (\text{A.8})$$

where $V_t = 2\pi^2 \kappa_a R_{geo} a^2$ is the volume of the tore [13]. By assuming that $n_D = n_T = \bar{n}_e/2$, replacing the expression of V_t , and approximating $\langle \sigma v \rangle_{DT} \approx 1.1810 \times 10^{-24} \hat{T} \text{ m}^3 \text{s}^{-1}$ through a polynomial fit for temperatures in the 10.3-18.5 keV range [13], one can get that

$$P_{fus} = C_{fus} \kappa \epsilon^2 R_{geo}^3 (\bar{n}_e \hat{T})^2, \quad (\text{A.9})$$

with $C_{fus} = 17.59 \cdot q \pi^2 \cdot 1.18 \cdot 10^{-24} \cdot 10^{2.19}/2 \approx 1.63 \cdot 10^{-3}$. To get the expression of P_{fus} in terms of R_{geo} and B_t instead of the plasma pressure $\bar{n}_e \hat{T}$, one can use the definition of $\beta\%$ and β_N . First, we express $\beta\%$ in a convenient form, such as:

$$\beta\% = C_\beta \frac{\bar{n}_e \hat{T}}{B_t^2}; \text{ with } C_\beta = 4 \cdot 100 \cdot \mu_0 \cdot 10^{19} \cdot 10^3 q \approx 0.805. \quad (\text{A.10})$$

Therefore, $\bar{n}_e \hat{T} = C_\beta^{-1} C_I \beta_N B_t^2$. Now, we use this to re-express Eq. (A.9) as

$$P_{fus} = \frac{C_{fus} C_I^2}{C_\beta^2} \cdot \frac{\kappa_a \epsilon^4}{q_{95}^2} \beta_N^2 R_{geo}^3 B_t^4. \quad (\text{A.11})$$

We have derived Eq. (3.5). To derive Eq. (3.6), it is necessary to think about the power balance in equilibrium at steady state. This means that the total plasma heating sources P_{hss} is equal to the power loss P_{loss} ; namely,

$$P_{hss} = P_\Omega + P_\alpha + P_{aux} = P_{loss} = P_{rad} + P_{l,th}. \quad (\text{A.12})$$

Here, P_Ω is the ohmic heating (often neglected), P_α is the energy carried by the alpha particles that are fully contributing to the D-T fuel, P_{aux} is the auxiliary heating power, P_{rad} is the radiated power, and $P_{l,th}$ is the power lost due to transport through the LCFS [13]. In order to have an explicit expression for the radiative losses, one needs to consider specific characteristics of the tokamak, like the plasma facing components [92], [93]. It is for this reason, that is preferable to parametrize the expression of the

radiative losses with a coefficient, $0 \leq \gamma_{rad} \leq 1$, as $P_{rad} = (1 - \gamma_{rad})P_{hss}$. From this, one gets from the power balance that

$$P_{hss} = (1 - \gamma_{rad})P_{hss} + P_{l,th}, \quad (\text{A.13})$$

meaning,

$$P_{l,th} = \gamma_{rad} (P_\Omega + P_\alpha + P_{aux}). \quad (\text{A.14})$$

If one neglects the ohmic heating, and makes use of $P_{fus} = \lambda P_\alpha$ and $Q = P_{fus}/P_{aux}$, then, one obtains the power loss due to transport in the form of

$$P_{l,th} = \gamma_{rad} P_{fus} \left(\frac{1}{Q} + \frac{1}{\lambda} \right). \quad (\text{A.15})$$

It is now time that we make use of the energy confinement time, which is defined as [89]

$$\tau_{E,th} = \frac{1}{P_{l,th}} \cdot 3V_t \hat{T} \bar{n}_e, \quad (\text{A.16})$$

where it has been assumed that the electron temperature is equal to the ion temperature [13]. By making use of the explicit expression of the torus volume, Eq. (A.9), and Eq. (A.15) one gets

$$\bar{n}_e \hat{T} \tau_{E,th} = 6\pi^2 \left[\gamma_{rad} C_{fus} \left(\frac{1}{\lambda} + \frac{1}{Q} \right) \right]^{-1}. \quad (\text{A.17})$$

We now take the scaling law of the energy confinement time, shown in Eq. (1.1),

$$\tau_{E,th} = \alpha_0 \cdot I_p^{\alpha_I} \cdot B_t^{\alpha_B} \cdot \bar{n}_e^{\alpha_n} \cdot P_{l,th}^{\alpha_P} \cdot R_{geo}^{\alpha_R} \cdot \kappa_a^{\alpha_\kappa} \cdot \epsilon^{\alpha_\epsilon} \cdot M_{eff}^{\alpha_M},$$

to multiply it with $\bar{n}_e \hat{T}$, replace I_p with Eq. (A.2), and $P_{l,th}$ with Eq. (A.15); namely,

$$\bar{n}_e \hat{T} \tau_{E,th} = \alpha_0 \cdot \hat{T} \cdot \bar{n}_e^{\alpha_n+1} \left(\frac{C_I}{q_{95}} \epsilon^2 B_t R_{geo} \right)^{\alpha_I} \cdot B_t^{\alpha_B} \cdot R_{geo}^{\alpha_R} \cdot \kappa_a^{\alpha_\kappa} \cdot \epsilon^{\alpha_\epsilon} \cdot M_{eff}^{\alpha_M} \cdot \left[\gamma_{rad} P_{fus} \left(\frac{1}{\lambda} + \frac{1}{Q} \right) \right]^{\alpha_P} \quad (\text{A.18})$$

which then can be simplified by replacing \bar{n}_e with n_N , and $\bar{n}_e \hat{T}$ with β_N to then equate with Eq. (A.17); such as:

$$[C \cdot \Gamma(Q)]^{-1} = \alpha_0 \cdot R_{geo}^{\gamma_R} \cdot B_t^{\gamma_B} \cdot P_{fus}^{\alpha_P} \cdot M_{eff}^{\alpha_M} \cdot \kappa_a^{\alpha_\kappa} \cdot \epsilon^{\gamma_\epsilon} \cdot n_N^{\alpha_n} \cdot q_{95}^{-\gamma_I} \cdot \beta_N, \quad (\text{A.19})$$

Which is Eq. (3.6). Here, the exponents γ_x are:

$$\begin{aligned}\gamma_I &= 1 + \alpha_n + \alpha_I, & \gamma_R &= \alpha_R + \alpha_I - \alpha_n, \\ \gamma_\epsilon &= 1 + \alpha_\epsilon + 2\alpha_I, & \gamma_B &= \alpha_B + \alpha_n + \alpha_I + 2.\end{aligned}\tag{A.20}$$

Moreover,

$$\Gamma(Q) = \left[\gamma_{rad} \cdot \left(\frac{1}{\lambda} + \frac{1}{Q} \right) \right]^{\alpha_p+1}, \text{ and, } C = \left(\frac{10}{\pi} \right)^{\alpha_n} \cdot \frac{C_I^{\gamma_I} \cdot C_{fus}}{6\pi^2 C_\beta}. \tag{A.21}$$

It is possible to refine the analysis by considering the alpha-particle dilution, different ion and electron temperatures, or different density profiles [13]. However, for the purpose of this chapter, it is not necessary to implement these changes. By taking into account Eq. (A.11), and Eq. (A.18) it is clear how the relation reduces to an expression involving the engineering research variables, with β_t , the prescribed geometric coefficients and effective mass.

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