AUTOMATIC CLASSIFICATION OF PLASMA STATES IN AN ECR-TYPE ION SOURCE*

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Abstract

In this paper we present a methodology to infer the state of the plasma in an ECR source without using any sensor that modifies its behaviour. For this purpose, machine learning techniques are explored. In a first stage a characterisation experiment is carried out in which the different states of the plasma are detected, using clustering algorithms. Subsequently, a supervised learning paradigm is adopted to train a neural network that is capable of determining the state of the plasma at different working states. The control data: delivered RF power and gas flow, together with the data that can be measured without altering the plasma: incident power, reflected power and plasma luminosity, are provided to the system as an input, in order to achieve the state detection. Moreover, good results can also be achieved without measuring luminosity, which cannot be easily measured when the ECR source is the start of an injector. This methodology has been applied to a low-power ECR source in which low-density hydrogen plasmas are generated at the IZPILab laboratory of the University of the Basque Country.

INTRODUCTION

Electron cyclotron resonance ion sources (ECRIS) are now widely utilized for ion production in both basic research and industrial applications due to their dependability and ability to generate multiply charged ion beams from most stable elements. This widespread adoption is attributed to their consistent performance and versatility across various fields [1].

These sources generate plasma that undergoes state changes over time, necessitating precise measurements to enable effective operation. Furthermore, it is crucial to perform these measurements non-intrusively to avoid interference with the plasma dynamics. This necessity forms the primary motivation for developing the methodology presented in this paper, which aims to infer the state of the plasma in an ECRIS source without employing any sensors that could alter its behavior. This is achieved through the application of advanced Machine Learning (ML) techniques.

Ion Source Operational Details

The source designs and implementations used for the experiments are comprehensively described in [2]. These designs are tailored for low current industrial and bioapplications, leveraging Electron Cyclotron Resonance (ECR) principles. The main design parameters are summarized in Table 1. Although the table specifically references H2, the ion source is versatile and can operate with other gases, such as Helium, Nitrogen, or any other elemental gas for ion production.

Table 1: Main design parameters of PIT30 ion source.

ECRIS parameters	
Microwave frequency	3 GHz
Microwave power	<500 W
Gas mass flow	<5 sccm (H_2)
Magnetic field	110 mT
Extraction voltage	≤30 kV
Beam current	<50 μA (H^+)
Beam emittance	<0.2 mm mrad

Fig. 1 depicts a CAD-rendered cross-sectional schematic of the plasma chamber, assembled from standard components. This chamber is configured as a circular waveguide, and for the chosen operating frequency, the smallest commercial diameter suitable as a resonant cavity within the CF flange system was DN 63. To produce the required magnetic field within the chamber for electron resonance, permanent magnets were utilized. The magnetic field strength was determined using the equation for the resonant frequency of a free electron in a magnetic field ($B = 2\pi f \frac{m}{e}$), where B represents the magnetic flux density, f is the frequency of the microwaves, and m and e are the mass and charge of the electron, respectively. For the intended 3 GHz microwaves, this results in an approximate field of 110 mT. To achieve this, a Halbach array consisting of eight permanent magnet bars was designed to create an axial magnetic field aligned with the plasma chamber.

In this source, both the power of the signal transmitted to the chamber (or RF power) and the gas flow can be adjusted. The signal power can be varied using a signal generator capable of producing a variable power signal of up to 1 mW. This signal is subsequently amplified by a fixed-gain amplifier. Initially, an amplifier that could amplify the signal from the generator up to 500 W was used. The hydrogen flow is regulated by a flow controller, allowing independent control of the hydrogen flow up to 5 sccm (standard cubic centimeters per minute under conditions of 273 K temperature and 1.01 bar pressure).

Plasma Chamber Dynamics

The gas transferred to PIT30 is molecular hydrogen (H_2). In the processes that take place in the hydrogen plasma, in addition to protons (H^+), other ionic species such as H_2^+ and H_3^+ are generated. Figure 2 shows the surfaces that define

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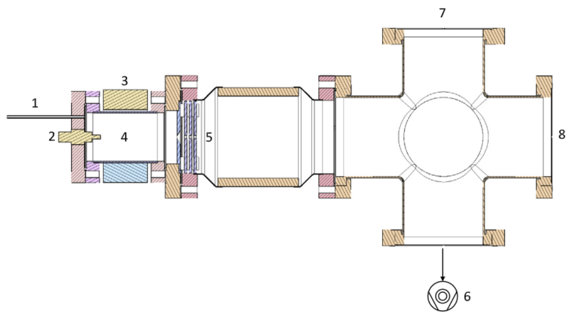

Figure 1: Cross section of a CAD drawing of the proposed plasma chamber made from standard CF components. (1) gas inlet, (2) RF port, (3) magnetic structure, (4) plasma chamber,(5) extraction electrodes, (6) Turbomolecular pump port, (7) pressure sensor (8) Faraday cup/ Scintillator screen port. The entire assembly shown is 600 mm long.

the ionic densities as a function of the two variables (RF power and gas density), and Figure 3 shows the regimes in which each species is predominant. We consider the plasma has changed its state when the predominant species in the plasma changes.

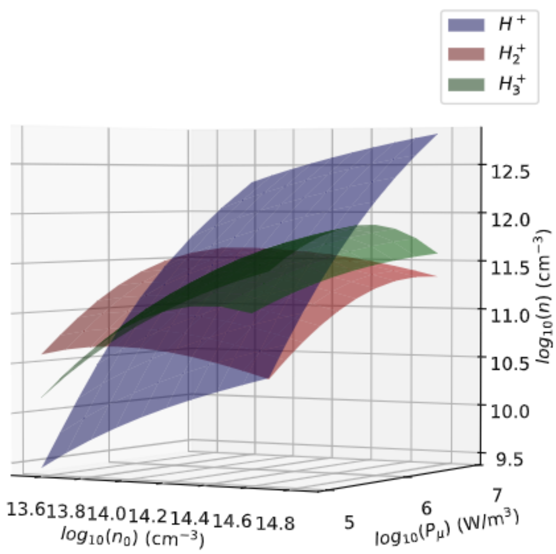

Figure 2: Density of H^+ (blue), H_2^+ (red), and H_3^+ (green) as a function of power density and neutral gas density.

Experimental Data Insights

The dataset used to initially train the algorithms consists of gas and power sweeps in the accelerator source, so that for an introduced power, two gas sweeps were performed, as shown in Fig. 4. Each measurement was always taken in the steady-state regime, thus avoiding introducing noise into the measurements. The following measurements were taken:

- *Time (s)*: Time in seconds, referring to the time interval of each measurement.
- *Reflected (W)*: Reflected power in watts, indicating the

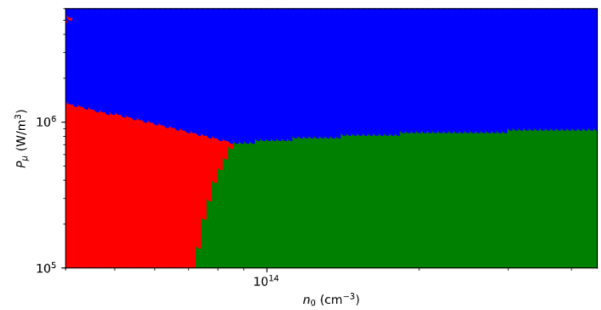

Figure 3: Map of the regions where each species predominates. Blue where protons predominate, red where $H^+{}_2$ predominates and green where $H^+{}_3$ predominates.

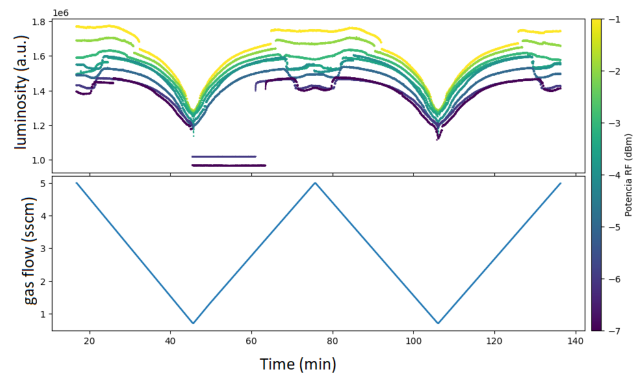

Figure 4: Representation of the acquired data.

amount of power that is not transferred to the plasma and is reflected back to the power source.
- *Forward (W)*: Forward power in watts, measuring the amount of power emitted by the power source towards the plasma.
- *Adaptation (W)*: Adaptation of the signal injected into the source.
- *Noise (W)*: Noise in watts, quantifying the random perturbation affecting the measurement signals.
- *Gasflow (sccm)*: Gas flow in standard cubic centimeters per minute, specifying the volume of gas passing through the system per unit of time.
- *Rfpower (W)*: RF power in watts, referring to the radiofrequency power used in the source.
- *Frequency (Hz)*: Frequency in Hertz, describing the oscillation rate of the injected signal.
- *Luminosity (u.a.)*: Measured luminosity of the plasma coming from the source, measured in arbitrary units.

If the cross-correlation of these data is studied, it is observed that there is a positive correlation (0.67) between the beam luminosity and the adaptation at the source input. This relationship will be useful later, as it implies that analyzing changes in one of the variables is almost equivalent to analyzing changes in the other, allowing us to eliminate one of the variables without losing significant information. Since luminosity is not always an accessible variable (especially in accelerators where the particle source is already fully

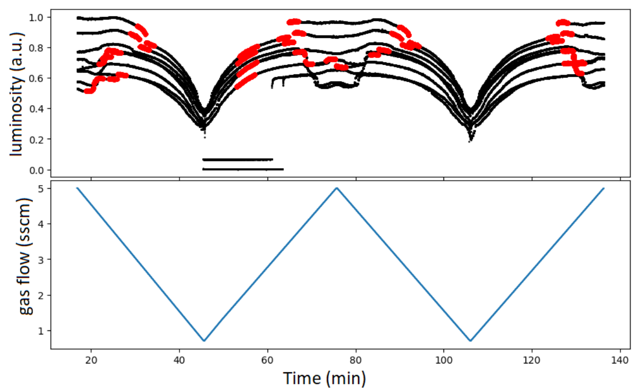

Figure 5: Detected jumps (in red) with configuration 1.

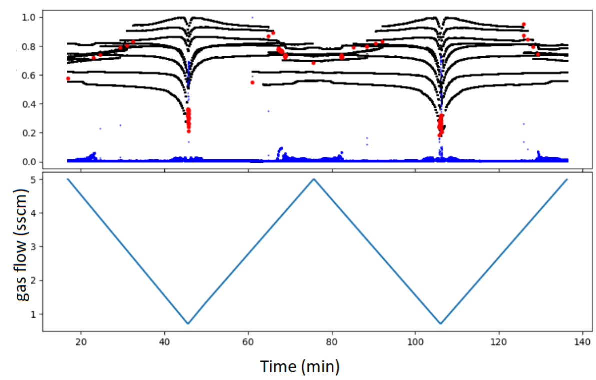

Figure 6: Detected jumps (in red) with configuration 2. The adaptation is shown in black, and the noise in blue..

integrated), this information suggests that substituting luminosity with adaptation could enable non-intrusive operations in the accelerator.

IDENTIFYING PLASMA STATE JUMPS

As previously explained, we designed a method that detects changes in the plasma state of the ion source and classifies them into one of three possible states. Therefore, the main challenge involves two tasks: detecting these changes and classifying them.

The easiest way to find state transitions is to analyze luminosity as a function of time. Whenever the plasma changes state, a sudden change in beam luminosity is observed. Therefore, the analysis of luminosity growth provides the necessary information to locate these transitions.

Firstly, an algorithm is proposed that performs linear regressions for every interval of n points. The slope of this line is proportional to the average growth of luminosity in that interval. Next, the difference in growth between continuous intervals is calculated and compared to the average difference of their neighbours, thereby avoiding issues due to isolated very high or low values. This allows us to identify regions where abrupt changes in growth occur compared to the local growth rate. Finally, the intervals that meet the requirements are selected.

As explained earlier, luminosity and adaptation are correlated variables; therefore, substituting one for the other allows for a similar analysis of plasma behavior. From now on, *configuration 1* will refer to the use of luminosity as the variable, while *configuration 2* will indicate that luminosity has been substituted by the adaptation. In Fig. 5 and Fig. 6, the results of this method in detecting state changes with configuration 1 and configuration 2, respectively are shown.

TECHNIQUES FOR CATEGORIZING PLASMA TRANSITIONS

Once the state changes are detected, we will attempt to classify them into one of three possible states using various algorithms: k-means, Random Forest and neural networks. We will then compare their performance, using the F1-score, to determine the most effective approach.

k-means

Initially, the k-means clustering algorithm is applied [4], utilizing features derived from windows of points around each identified jump. The variables and parameters used to train the k-means algorithm include: Adaptation, Luminosity, Maximum Luminosity Change, Mean Gas Change, Gas Flow, and RF Power. The optimal number of clusters is four, although initially a classification into three groups was considered. This additional fourth cluster has proven crucial for capturing false positives within the dataset.

The results presented in Fig. 7 effectively illustrate the ability of the k-means algorithm to accurately identify and classify jumps in configuration 1.

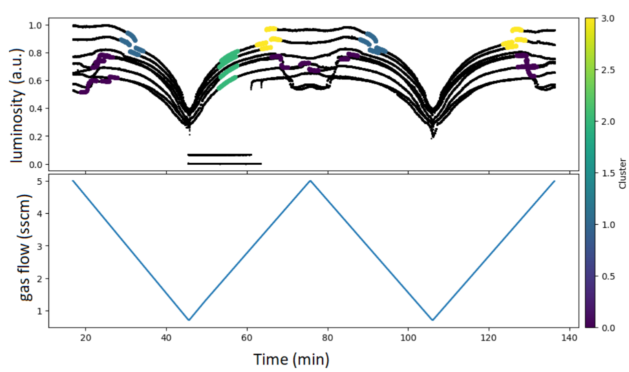

Figure 7: Final result of the k-means algorithm in classifying the detected jumps in configuration 1. False positives are shown in green.

Fig. 8 displays the results applied to configuration 2. Although not as precise as when luminosity is included among the variables, due to the correlation between adaptation and luminosity, the algorithm still manages to detect and classify the majority (78.3%) of the jumps adequately.

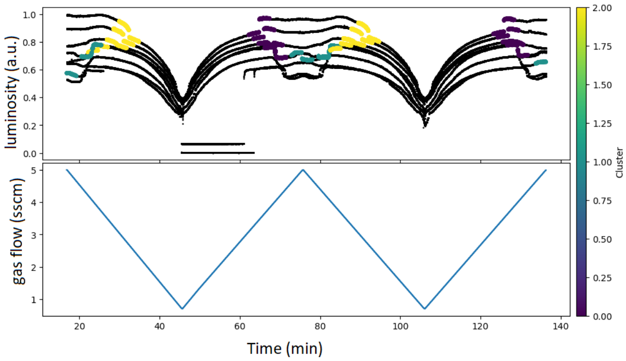

Figure 8: Final result of the k-means algorithm in classifying the detected jumps in configuration 2.

Random Forest

After experimenting with the k-means algorithm [3], we opted to try a supervised learning approach using the Random Forest algorithm to classify the data.

To optimize the model's performance, it was configured with the following parameters: number of trees set to 10, maximum depth of the trees set to 5, and the criterion for the quality of the splits set as Gini.

To test de performance a cross-validation was conducted. This process involved dividing the complete dataset into five folds. The model was trained and evaluated five times, each time with a different fold designated as the test set and the remaining as training sets. An F1-score result of 98% was achieved with configuration 1, and 97% with configuration 2.

Neural Networks

Finally, the use of neural networks [5] is proposed as a solution to the classification problem. Various types of networks have been explored, with sequential networks and Recurrent neural networks (RNN) proving to be the most effective.

To train the sequential network, the data were split into training and test sets, using 20% of the data for testing. After experimenting with various configurations, the highest-performing network was set up as follows: a flattening layer, followed by a first dense layer with 512 neurons using the ReLU activation function. The second and third dense layers have 256 and 128 neurons, respectively. The output layer uses the softmax activation function. A F1 Score of 76% was achieved with configuration 1, and a F1 Score of 64% with configuration 2.

The RNN model was reconfigured to simplify its structure and adjust its performance. The updated features of the model are as follows: An LSTM layer with 200 hidden units that processes input sequences, where each sequence consists of 1000 time steps, each with 10 features. Additionally, there is a dense output layer with 3 units, utilizing the softmax activation function. A F1 Score of 53.1% was obtained with luminosity, and an F1 Score of 53.9% was obtained without luminosity.

Clearly, the sequential network is much more accurate than the RNN. However, we can see that this network achieves very similar results when classifying points with and without luminosity, indicating that with more data, it could be a good solution for performing non-intrusive classification.

Table 2: Comparison of the F1-scores of all the algorithms

	Random Forest	**Sequential NN**	**RNN**
Config. 1	98%	76%	53%
Config. 2	97%	64%	54%

CONCLUSION

In this paper, a method has been designed to detect state changes in the plasma of a particle accelerator source. The use of ML has been explored to achieve an automatic identification of the injector's state. Two alternative methods have been developed to detect plasma state transitions, including the possibility of doing so without using luminosity, since obtaining measurements of this variable is very challenging once the accelerator is fully completed. Additionally, it has been verified that the unsupervised learning algorithm k-means is effective in classifying state transitions when luminosity is included, though it is not very accurate when this information is unavailable. Therefore, the use of a Random Forest algorithm has been proposed for these cases. Moreover, neural networks have also been proposed as a solution to the problem and the best architectures have been studied to achieve the most effective classification. Table 2 shows a quick comparison of the F1-scores of all the algorithms

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