# Real-time Diagnostics of Cold Atmospheric Pressure Plasmas using Machine Learning

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**Abstract:** Real-time diagnostics of atmospheric pressure plasma jets (APPJs) can be challenging due to need for complicated experimental setups or time-consuming data processing. In this work, we instead utilize large datasets of easy-to obtain measurements of information-rich signals, such as optical emission spectra and electroacoustic emission, to obtain real-time estimates of operation-relevant parameters.

**Keywords:** Cold atmospheric plasma, Diagnostics, Machine Learning, Optical Emission

## 1. Introduction

Cold atmospheric pressure plasmas (CAPs) are a class of cold plasma devices increasingly used in medical applications and materials processing [1]. However, CAPs are extremely sensitive to disturbances. For example, discharge characteristics can considerably vary with changing external conditions, such as ambient humidity [2], and the properties of the treated substrate [3]. Moreover, CAPs can undergo mode transitions, which substantially change the discharge properties of the plasma along with its corresponding effects [4]. It is therefore of key interest to have effective real-time diagnostics of the discharge parameters. Particularly in a medical context, the repeatability of the treatment essential. This further motivates a need for effective diagnostics of disturbances so that deviations from nominal operating conditions can be monitored and mitigated.

Common methods of direct diagnostics can be limited for implementation in real time. Methods ~~for~~ such as laser-induced fluorescence (LIF) [5], mass-spectroscopy [6], and spontaneous Raman scattering [7] can yield crucial information about the discharge properties including species concentrations and gas temperatures. However, such methods rely complicated and expensive experimental setups which can be difficult to reconcile with flexible hand-held treatment methods commonly used in plasma medicine. On the other hand, easy-to-obtain discharge emissions signals such as optical emission spectra (OES) and electroacoustic emission are rich in information but are difficult to interpret. For example, obtaining rotational and vibrational temperatures from OES requires generation and fitting of synthetic spectra [8]. Due to the numerous fitted parameters this kind of analysis can take several seconds up to a few minutes, deterring its use in real-time.

Machine learning (ML) methods have found success in variety of applications including natural language processing, image recognition and real-time diagnostics of low-pressure etching [9]-[11]. ML methods leverage large datasets to discover and compactly represent relationships between variables [12]. In this context, the information-rich emission signals from CAPs are particularly suitable for potential ML applications. Therefore, using ML models otherwise difficult-to-obtain quantities can be estimated.

In this work, we demonstrate the applicability of ML methods for real-time diagnostics of CAPs. Utilizing ML methods, we relate optical emission spectra to quantities obtained by independent measurements or by processing large quantities of data offline. We then demonstrate the obtained ML models can be used for real time diagnostics of operation-relevant parameters such as rotational and vibrational temperatures and distinguishing between dielectric and conductive substrates.

## 2. Experimental Setup and Methods

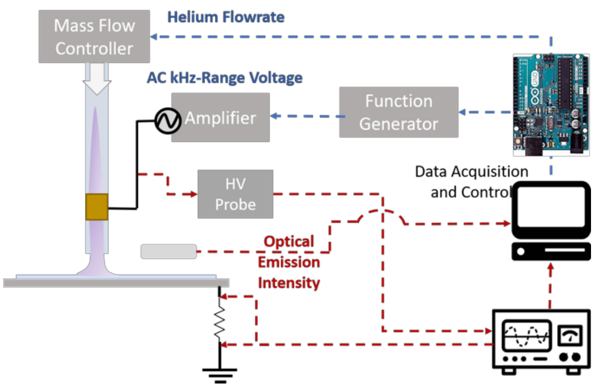


*Figure 1 - Experimental atmospheric pressure plasma jet (APPJ) setup with data acquisition signals shown in red and actuation signals shown in blue.*

We utilize the atmospheric pressure plasma jet (APPJ) system depicted in Figure 1 for experiments. The APPJ is excited with AC voltage at 20 kHz. A PI controller maintains the dissipated power, manipulating the applied voltage in a range of 6-10 kV peak-to-peak. The He flow rate is adjusted using a mass flow controller at range of 1-3 slm. A borosilicate microscope cover slip is placed under the discharge as the dielectric substrate, and a metal plate doubles as ground and the conductive substrate. An, optical emission spectrometer (Ocean Optics USB2000+) is utilized to collect spectra. A microcontroller (Arduino UNO) and a single board computer (Raspberry PI) are used to coordinate and automate actuation and data collection.

We employ two basic ML methods: *least absolute shrinkage and selection operator (LASSO) linear regression* [13] for estimating rotational and vibrational temperatures and, *k-Means clustering* [14] for classifying substrate type. To train the ML models we utilize a data-set consisting of 1500 samples of normalized OES peaks of N2(C-B) transition (364-390 nm), collected under varying operating power, flow and substrate type. We analyzed the OES peaks, offline using MassiveOES [15] to fit rotational and vibrational temperatures. Together, the fitted temperatures and the OES spectra are used to fit a linear regression model to predict rotational and vibrational temperatures in real-time. The OES spectra alone are used in the *k*-Means clustering algorithm to classify the substrate type.

## 3. Results

### a. Rotational and Vibrational Temperature Estimation

We utilize a linear model with polynomial basis of third order for the estimation of rotational and vibrational temperatures. After the model is fitted, its predictive performance is evaluated against an independent test dataset collected over a range of

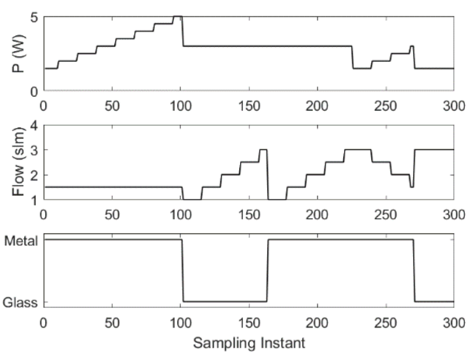


*Figure 2 – Operating conditions (applied power, He flow and substrate type) used to test the linear regression algorithm.*

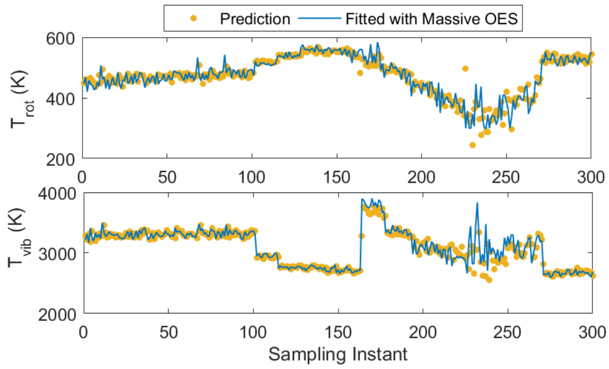


*Figure 3 – Rotational and vibrational temperatures fitted using Massive OES and predicted using linear regression.*

operating conditions shown in Figure 2. The corresponding estimates of rotational and vibrational temperatures predicted by the linear regression model are shown in Figure 3 alongside values fitted offline with Massive OES.

Figure 3 shows that the linear regression algorithm is capable of predicting the rotational and vibrational temperatures in real-time with reasonable accuracy. We observe some notable deviations around sampling instants 210-250 where the flow is decreased while the applied power is increased. The increase in noise observed under these conditions can be attributed to the discharge moving on the metal substrate causing OES probe to fall out of focus. We quantify the performance of the linear regression model with an $R^2$ value of 0.79.

### b. Substrate type detection

We utilize *k*-Means clustering to cluster the OES spectra collected into two distinct classes corresponding to dielectric and conductive substrates. *k*-Means algorithm describes two clusters in terms of their canter points or *centroids*. Figure 4 shows that the centroids of the OES spectra clusters corresponding the glass and metal substrates.

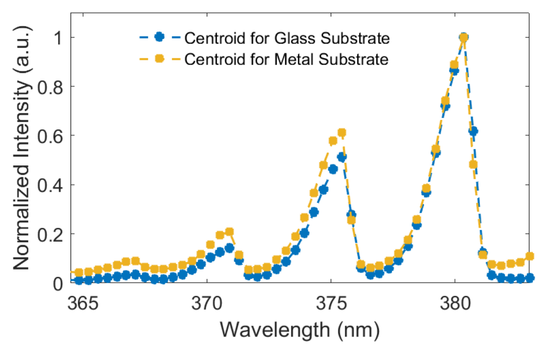


*Figure 4 – Centroids of OES spectra obtain from the k-Means algorithm corresponding to glass and metal substrates.*

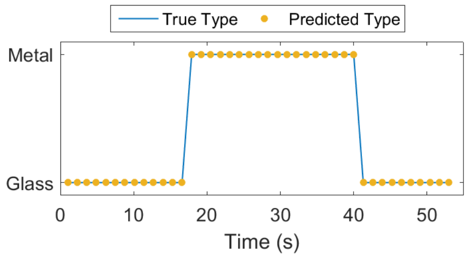


*Figure 5 – Performance of the k-Means algorithm in detecting glass and metal substrates in real time.*

Clusters determined with the *k*-Means algorithm are used in real-time to assign new OES measurement to either of the two classes. In this way, the substrate type is detected in real-time. Figure 5 shows the performance of the *k*-Means algorithm in determining the substrate type as the APPJ is translated back and forth across the dielectric and conductive substrates. Notably, the substrate type is detected with perfect accuracy. We note that the transition between glass and metal substrate results in a drastic change in the discharge properties and therefore is comparatively easy to detect. Nevertheless, this demonstration still serves to show how discrete events can be detected in real time using ML methods.

## 4. Conclusions and Future Work

We demonstrate the potential for ML methods for real-time diagnostics of CAPs. The relatively simple ML algorithms we have used achieve remarkable performance in estimating rotational and vibrational temperatures of the discharge in real time and in detecting glass and metal substrates

ML methods have great potential for applications in CAPs. More specifically, they can be used to correlate other difficult-to-obtain quantities such as species concentration and electric field strengths to easily obtained measurements such as optical and electroacoustic emissions. A major challenge in broad application of ML methods is the availability of large datasets. We note the importance of automation strategies for data collection and actuation for constructing large dataset enabling the use of ML methods.

Effective real-time diagnostics can be used to mitigate the variabilities observed in the discharge in real-time improving the reliability and repeatability of operation. ML methods can further be utilized to obtain complex input-output models of the discharge and help discover complex relationships among variables and uncover underlying physical phenomena. In a medical context, data-driven ML methods can be instrumental in developing patient-specific treatment protocols.

## 5. References

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