Learning-based Feedback Control for Dose Delivery with Atmospheric Pressure Plasma Jets Under Uncertainty

Angelo D. Bonzanini[1], Dogan Gidon[1], David Graves[1], and Ali Mesbah[1]

[1] *Department of Chemical and Biomolecular Engineering at UC Berkeley, CA, 94720, USA.*

Abstract: This work presents a learning-based model predictive control (LB-MPC) strategy for atmospheric-pressure plasma jets (APPJs) under uncertainty. The controller is designed such that it delivers a uniform dose while satisfying constraints that aim to mimic restrictions that ensure patient safety and comfort. Online learning from the data is incorporated via Gaussian process regression, thus improving the accuracy of the model. Finally, the power of this approach is experimentally demonstrated on an APPJ set-up.

Keywords: APPJ, MPC, Machine Learning, Gaussian Process, Uncertainty.

Atmospheric Pressure Plasma Jets (APPJs) are a class of cold atmospheric plasma devices with applications ranging from materials processing to medical applications. However, channeling this potential to practical use is extremely challenging due to their intrinsic variability and nonlinear behavior. For example, APPJs are subject to significant run-to-run variations, even when the experimental conditions are similar [1], while also exhibiting very steep axial and radial gradients in both temperature and species concentrations [2]. Consequently, for the effective use of such devices, it is imperative to be able to control their behavior in an automated manner. A useful tool to tackle such a problem is Model Predictive Control (MPC), which is an optimization-based control strategy able to handle multivariable systems subject to constraints [3], [4]. Even so, MPC is reliant on a good system model, which is generally unavailable for APPJs. In addition, uncertainties and disturbances in the plasma may cause it to exceed specified operating tolerances. These include, for example, temperature constraints put in place to avoid tissue damage and associated negative effects on patient safety and comfort in plasma medicine applications [5]. As a result, uncertainties and inaccuracies in the plasma, combined with exogenous disturbances, may compromise the constraint handling ability of MPC. This can be detrimental to safe and reproducible system operation.

To this end, we propose a learning-based MPC (LB-MPC) control strategy, which accounts for the effect of the uncertainties in order to ensure constraint satisfaction up to a user-defined level. Firstly, we formulate the problem with the objective of delivering a specified dose in the presence of constraints that mimic restrictions put in place to ensure patient safety and comfort. Secondly, we extend the MPC framework with a Bayesian learning feature to reduce model uncertainty in plasma dynamics and thus enhance the accuracy of the predictions. Specifically, Gaussian process (GP) regression lends itself particularly well for such an application, since it naturally defines the mean and variance of the predictions. This provision allows incorporation of the uncertainty of model predictions, and, by extension, to account for their effects [6]. Thirdly, we design the controller such that it has the ability to estimate and counteract deterministic disturbances such as change in tip-to-surface separation distance, which may not be accounted for by GP.

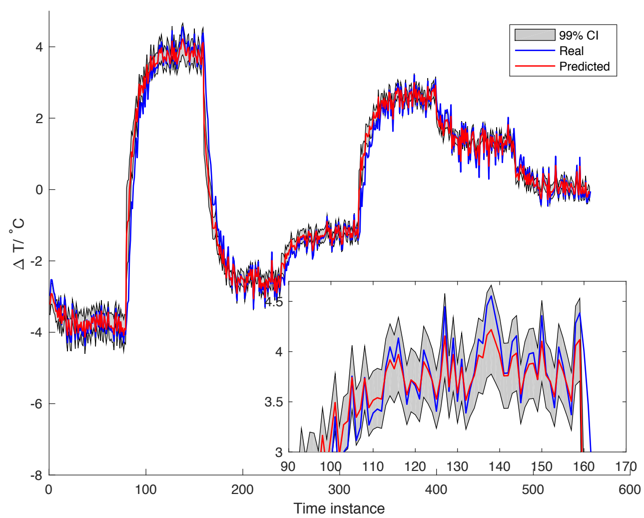

Figure 1: Prediction of test data using GP regression. The blue line indicates the data to be predicted, while the red line indicates the GP predictions. The shaded gray area is the 99% confidence interval of the GP predictions.

We illustrate the power of this approach in simulation and experiments for a kHz-excited APPJ in He described in [4]. We demonstrate that online learning improves the quality of model predictions and thus the performance of the controller. Deviations between the measured APPJ outputs (i.e., plant data) and the model along with previous APPJ

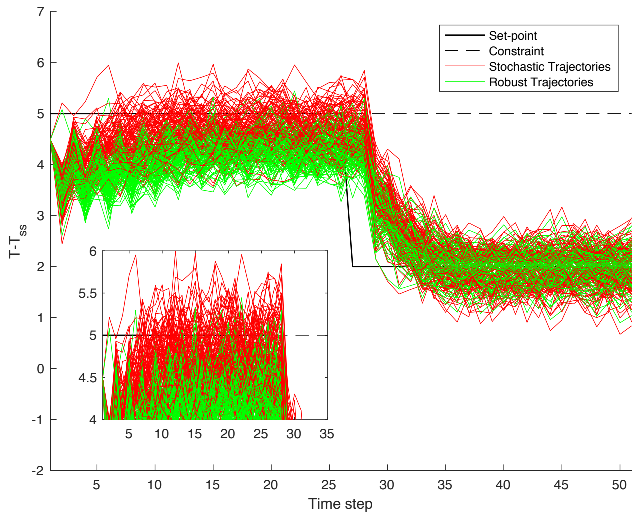

Figure 2: Evolution of the closed-loop states under 100 uncertainty realizations when the system is guaranteed to remain within the constraints (green) vs. when it is allowed to violate the constraints up to a pre-defined probability (red). The inset shows a more-detailed view of the operation close to the constraints.

inputs are used to train a GP regression algorithm in order to predict the plant-model mismatch. An independent data-set is then used to test the predictive capability of GP, as shown in Figure 1. In addition, GP naturally provides uncertainty bounds in the form of confidence intervals, which enable the controller to operate with enough safety margin so that it minimizes constraint violation. The choice of the degree of constraint violation is typically left to the user, who can either require that the constraints are satisfied at all times, or can define an acceptable level of constraint violation. This is verified by performing Monte Carlo simulations as shown in Figure 2. The goal is to follow a set-point (from $x = 5$ to $x = 2$) on substrate temperature that requires operation at the edges of the allowed region, while accounting for the effect of the uncertainties. Dose can therefore be delivered uniformly without exceeding the constraints set on temperature by more than the desired level, even when operation close to the constraints is required. Clearly, when the constraints have to be satisfied for all uncertainty realizations the controller ends up being more conservative, leading to worse performance than when some constraint violation can be tolerated. In both cases, however, GP does a good job in predicting the uncertainty, as illustrated by the fact that the system can track a set-point without any offset even in the presence of plant-model mismatch.

References

[1] J. Shin and L. L. Raja, "Run-to-run variations, asymmetric pulses, and long time-scale transient phenomena in dielectric-barrier atmospheric pressure glow discharges," *Journal of Physics D: Applied Physics,* pp. 3145-3154, 2007.

[2] M. Dünnbier, A. Schmidt-Bleker, J. Winter, M. Wolfram, R. Hippler, K.-D. Weltmann and S. .. Reuter, "Ambient air particle transport into the effluent of a cold atmospheric-pressure argon plasma jet investigated by molecular beam mass spectrometry," *Journal of Physics D: Applied Physics,* (2013).

[3] D. Gidon, D. B. Graves and A. Mesbah, "Effective dose delivery in atmospheric pressure plasma jets for plasma medicine: A model predictive control approach," *Plasma Sources Science and Technology,* pp. 85005-85019, 2017.

[4] D. Gidon, B. Curtis, J. A. Paulson, D. B. Graves and A. Mesbah, "Model-Based Feedback Control of a kHz-Excited Atmospheric Pressure Plasma Jet," *IEEE Transactions on Radiation and Plasma Medical Sciences,* pp. 129-137, 2017.

[5] R. Soloperto, M. A. Müller, S. Trimpe and F. Allgöwer, "Learning-Based Robust Model Predictive Control with State-Dependent Uncertainty," *6th IFAC Conference on Nonlinear Model Predictive Control,* pp. 442-447, 2018.

[6] C. E. Rasmussen and C. K. I. Williams, Gaussian processes for machine learning., Cambridge, MA: MIT Press, 2006.