LEARNING-BASED CONTROL: APPLICATIONS IN TREATMENT OF COMPLEX SUBSTRATES USING NON-EQUILIBRIUM PLASMAS

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Abstract Overview

Learning-based control can create unprecedented opportunities for control of non-equilibrium plasmas for treatment of complex substrates in applications such as plasma medicine and plasma catalysis. This work discusses two learning-based control strategies, namely learning-based robust nonlinear predictive control using Gaussian processes and sim-to-real transfer reinforcement learning, for control of the thermal effects of atmospheric-pressure plasma jets.

Keywords

Learning-based predictive control, Gaussian processes, Sim-to-real transfer reinforcement learning, Non-equilibrium plasmas.

Introduction

Non-equilibrium plasmas (NEPs) are weakly ionized gases typically generated in ambient conditions via the application of a modulated electric field to inert gases such as argon and helium. NEPs have recently gained increasing attention for treatment of heat and pressure sensitive (bio)materials in surface etching/functionalize-tion, environmental, and biomedical applications (Stoffels et al., 2008; Neyts et al., 2015). Some of the main challenges in process control of NEP applications arise from their inherent complexity and variability (Gidon et al., 2018; 2019). Firstly, the dynamics of NEPs are highly nonlinear and spatio-temporally distributed. NEP dynamics are challenging to model using first principles, and the resulting models are computationally prohibitive for real-time control applications. Secondly, the treatment effects of NEPs on complex surfaces, e.g., in plasma catalysis or plasma medicine, are currently poorly understood. And, thirdly, NEPs generally exhibit significant run-to-run variations and time-varying dynamics, whereby the NEP treatments carried out under identical conditions can yield vastly different outcomes.

This work discusses the unprecedented opportunities that learning-based control can create for feedback control of NEPs for treatment of complex substrates (Mesbah and Graves, 2019). We demonstrate the effectiveness of two learning-based control strategies, namely learning-based nonlinear predictive control and reinforcement learning, for control of the thermal effects of a class of NEP devices on substrates with non-uniform electrical and thermal properties.

Learning-Based Robust Nonlinear Predictive Control with State-Dependent Noise

We present a learning-based robust model predictive control (LB-RMPC) strategy for offset-free tracking of nonlinear systems under uncertainty. The problem setup considered here consists of a linear dynamic model with a

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nonlinear additive state-dependent noise, which is described using Gaussian process (GP) regression. GP regression allows for obtaining state-dependent uncertainty bounds. The GP model is trained online to eliminate the plant-model mismatch and reduce the system uncertainty, in particular in view of the time-varying characteristics of the target substrate.

We demonstrate the proposed LB-RMPC strategy on an atmospheric-pressure plasma jet (APPJs) with prototypical applications in plasma medicine and materials processing. The real-time control experiments indicate that the LB-RMPC strategy can effectively handle state constraints, while exhibiting a less conservative control performance compared to RMPC based on worst-case uncertainty bounds. Furthermore, online learning of the GP model allows for effectively handling the plant-model mismatch that arises from the variations in the thermal and electrical characteristics of the target substrate. We show that LB-RMPC holds great promise for safety-critical applications of APPJs, such as in plasma medicine, where plasma dynamics and plasma-substrate interactions are complex and hard to model using first principles, substrate characteristics are patient specific and can vary during the treatment (i.e., plant-model mismatch increases), and reliable state constraint handling is critical to safe and reproducible treatment.

Sim-to-Real Transfer Reinforcement Learning

A main challenge in model-based control of APPJs arises from the complexity of the plasma-substrate interactions. The plasma treatment of complex substrates is particularly sensitive to changes in the physical, chemical, and electrical properties of the substrate, which may vary considerably within and between target substrates. Here, we demonstrate the use of deep reinforcement learning (RL) for learning-based control of complex substrates with time-varying or non-uniform characteristics (Witman et al., 2019).

A lumped-parameter, physics-based model of the thermal dynamics of the plasma-substrate interactions is used to train a RL agent for regulating the substrate temperature. To enrich the training data and reduce the "reality gap" between the simulated and real-world environment, *dynamics randomization* (Peng et al., 2017) is used to systematically randomize the parameters of the physics-based model during the training process to account for unmolded process dynamics as well as the different dynamics the RL agent may encounter during the plasma treatment (i.e., due to variations in the substrate). The RL agent is designed based on an actor-critic algorithm that uses deep neural networks to approximate the actor policy and the value function (Mnih et al., 2016). Real-time control experiments indicate the effectiveness of the RL agent for regulating the thermal effects of the APPJ on the target substrate in the presence of significant changes in the electrical and thermal properties of the substrate. The results highlight the importance of dynamics randomization in successful *sim-to-real transfer learning* of RL agents.

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