Bayesian Optimization of Perovskite Solar Cells Made by Photonic Curing



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Introduction

OVAT

Motivation:

- Optimize Photonic Curing (PC), an industry-scale post-deposition process, in flexible perovskite solar cells (fPSCs) fabrication.
- lab-scale resources (limited time, 1-2 experimentalists) are unable to deal with the vast process variables of PC, e.g., pulse voltage, pulse length as well as precursor ink formulation.
- One-variable-at-a-time approach (OVAT) is impossible.

Method:

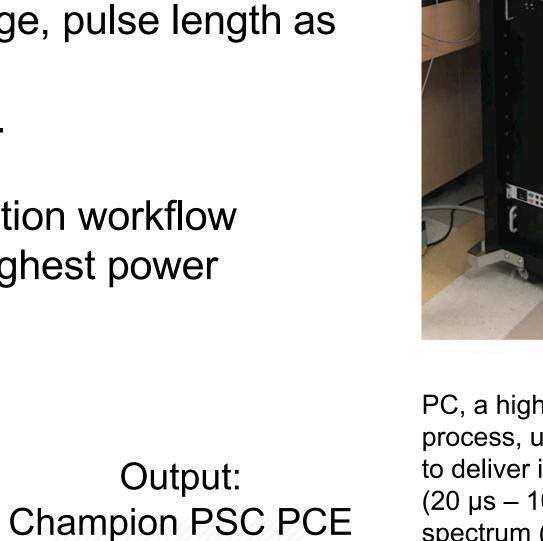
- Integrate Bayesian Optimization (BO) into PC optimization workflow
- Find the best variables producing the PSCs with the highest power conversion efficiency (PCE).

Challenge:

Non-ideal pre-defined variable range.

Input variable	Range (Interval)
MAPI concentration	1.3 – 1.6 M (0.1 M)
CH ₂ I ₂ vol%	$0 - 250 \mu L (50 uL)$
Pulse voltage	200 - 440 V (1 V)
Pulse length	1 – 20 ms (0.1 ms)

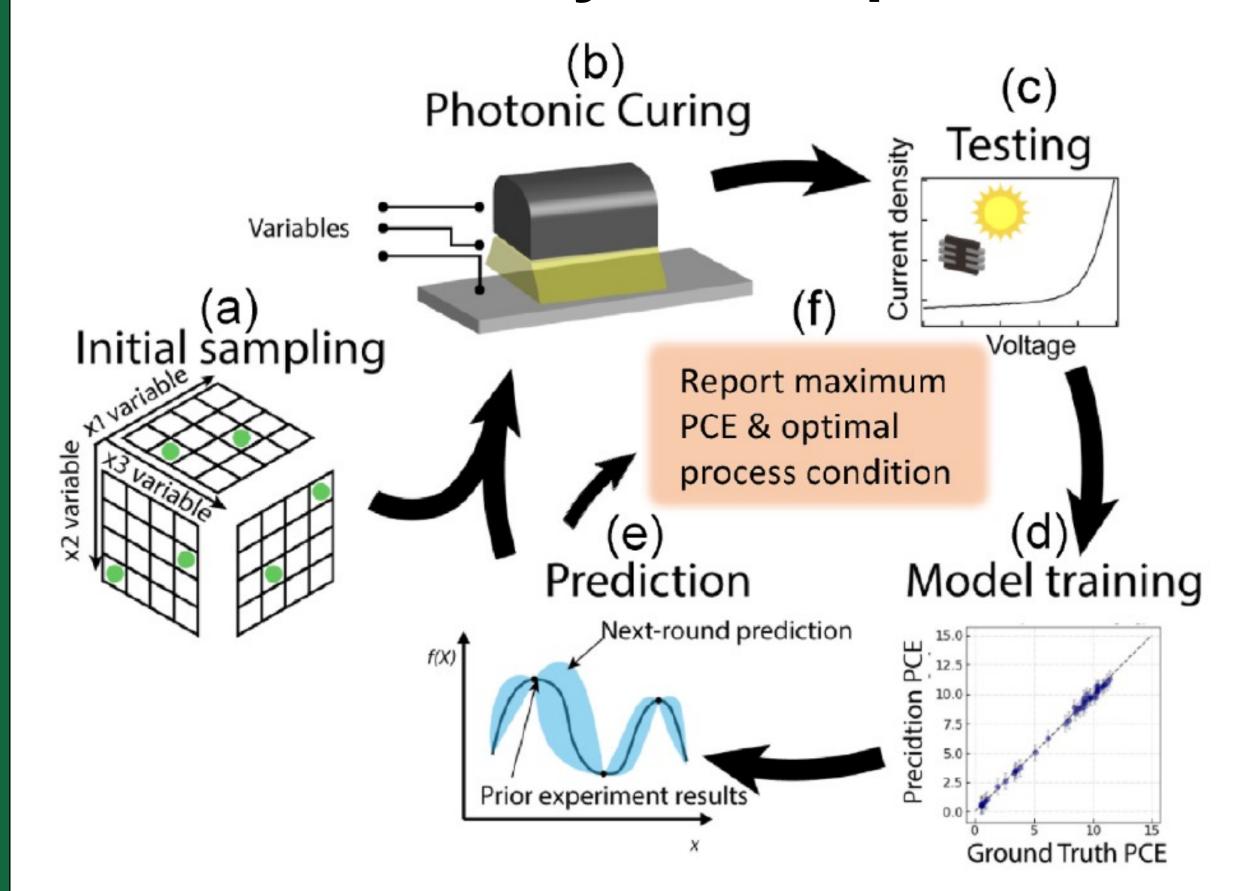




Output:

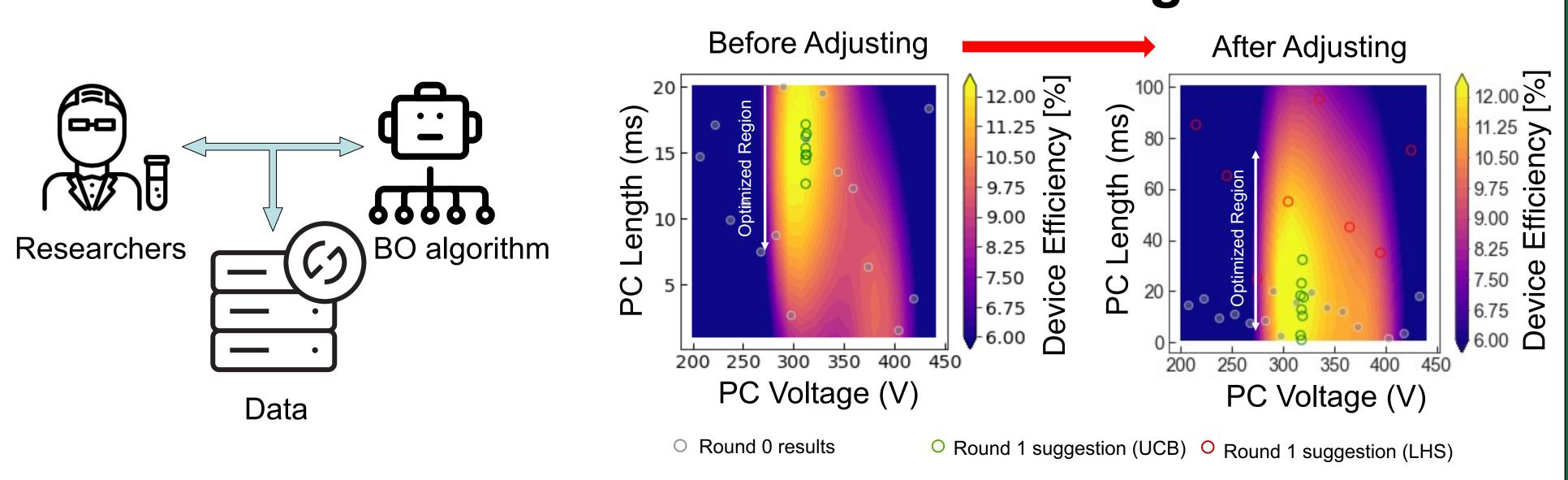
PC, a high-throughput large-area process, uses a flash xenon lamp to deliver intense photon pulses $(20 \mu s - 100 ms)$ with a broadband spectrum (200 nm – 1500 nm) has been reported to convert methylammonium lead iodide (MAPbl₃) precursor into a polycrystalline thin film.

Bayesian Optimization Workflow



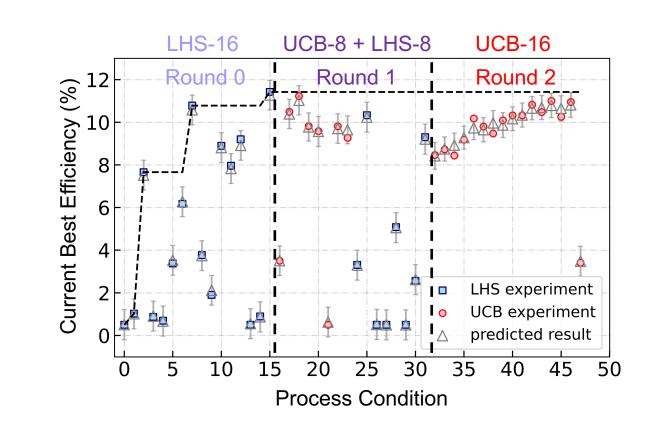
- a) Latin Hypercube Sampling (LHS) to generate 16 initial conditions.
- b) fPSCs are fabricated on Willow Glass® with the parameters decided by (a) or (c)
- c) Testing standard AM 1.5 G condition.
- d) Gaussian Process.
- e) Upper Confidence Bound (UCB) is our acquisition function to predict next round of 16 conditions.
- f) Iterations continue until the input parameters converged.

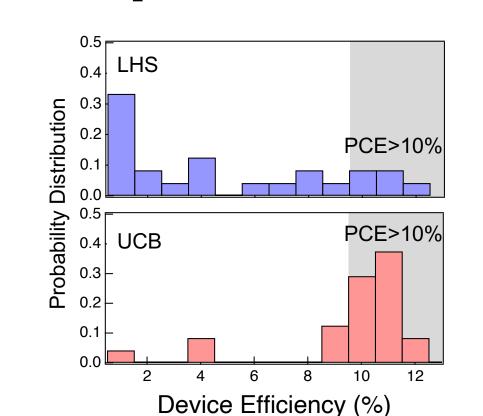
Human-Machine Interaction in Variable Range Selection



- Pre-defined variable ranges are critical because all follow-up experimental iterations will be done in these ranges.
- However, for a new optimization problem, these are often subjectively decided by the researchers.
- Here, we adopted dynamical parameter ranges based on researcher examining the contour plot feedback after each iteration.

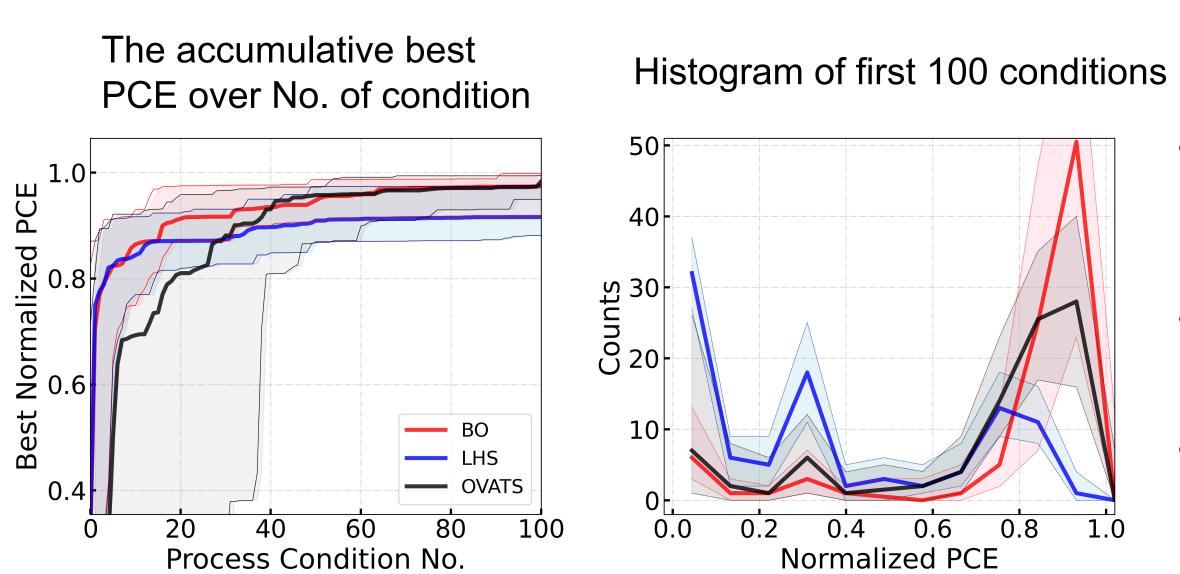
Device Optimization Results





- With the limited experimental budget of 48 conditions, we achieved a champion PCE of 11.42%.
- As expected, UCB has a higher success rate finding the conditions of PCE > 10%.

Virtual Benchmarking



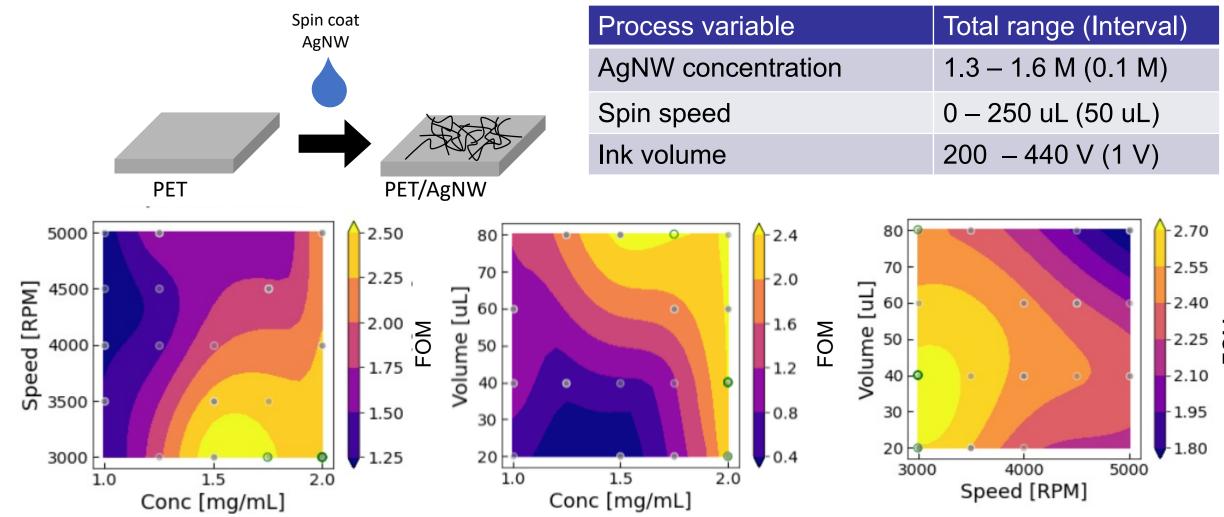
- A fully trained "teacher" model derived from all 48 experimental conditions is the benchmarking platform.
- Improving Device PCE: BO > LHS > OVAT
- Success rate finding > 0.9 normalized PCE:

BO > OVAT > LHS

All three approaches have been randomly iterated for 100 times to get the 5 – 95% confidence intervals.

Other Optimization Problems: Fast Convergence?

1. Optimize Ag nanowire (AgNW) deposition for transparent conductors



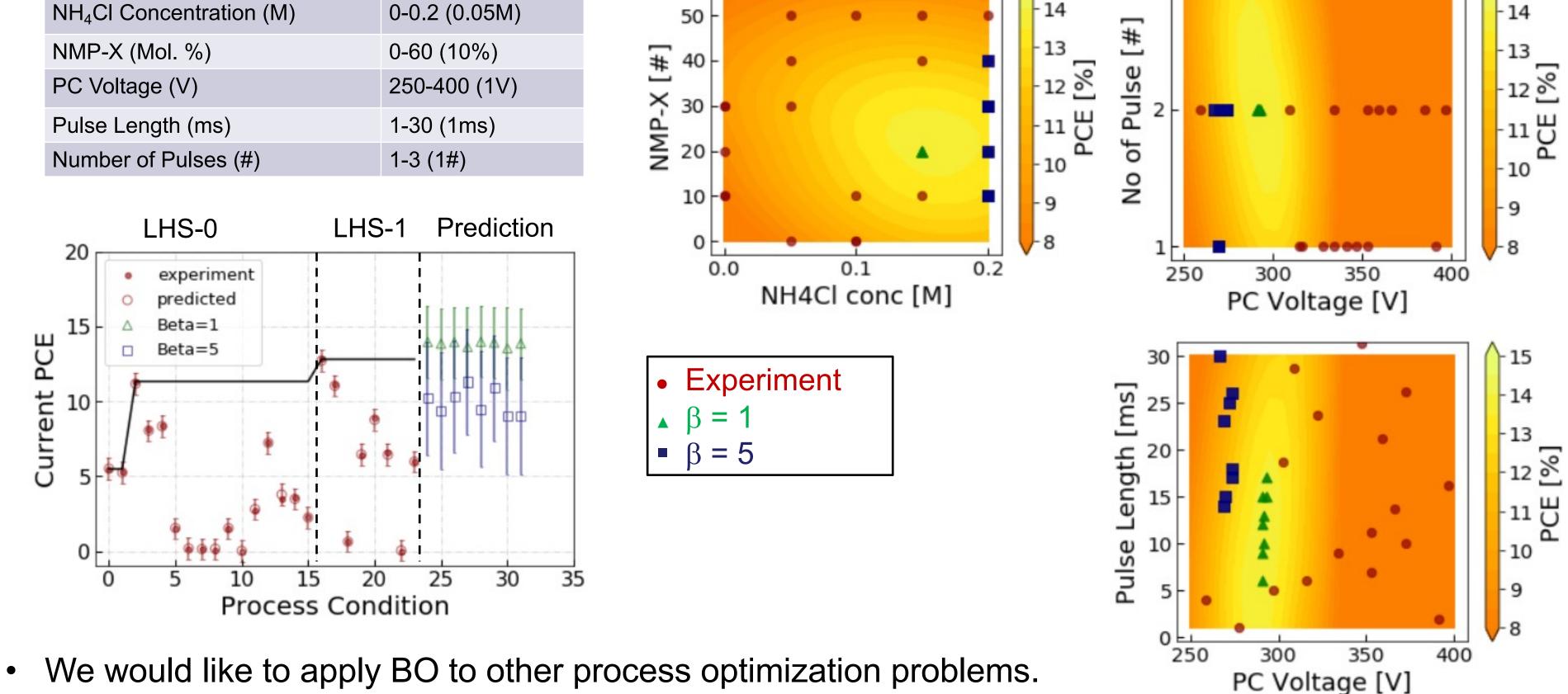
- 15 LHS conditions
- Next round converges.

	Co	nc(mg/mL) Sp	eed(RPM) Vo	lume(uL)
	0	2.00	3000.0	40.0
	1	2.00	3000.0	40.0
	2	2.00	3000.0	40.0
	3	2.00	3000.0	40.0
	4	1.75	3000.0	80.0
	5	2.00	3000.0	40.0
	6	2.00	3000.0	40.0
5	7	2.00	3000.0	40.0
•	8	2.00	3000.0	40.0
	9	2.00	3000.0	20.0

2. Optimize another perovskite formulation

Range (Interval)

Input variable



- Using UCB acquisition function with $\beta = 1$, two very different problems show convergence after LHS. Why?
- Problem too simple? Only one maximum.
- 2. Incorrect β values? How do we choose β? Should we not use UCB?
- 3. Is local penalization in batch optimization not strong enough?

Future Work

Experiment Process Variables Chemical Formulation etc

Bayesian Optimization Acquisition Function

- Local Penalization
- Surrogate Function
- How can we choose hyperparameters in BO to better suit specific experiments?
- How can we monitor the BO decision more objectively?
- How do we incorporate human intelligence and prior/transfer knowledge?

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