Differentiable Physics-based Greenhouse Simulation

A preliminary result Presentation

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Background

Motivation

- Accurate simulation model is required for greenhouse optimal control.
- Physics-based models are the most accurate class of model for greenhouse simulation. However, they're not differentiable.
- This limit the adaptability of those models and make them not compatible with some control algorithms.
- With the recent rise of automatic differentiation frameworks, it is possible to construct and implement a differentiable physics-based greenhouse simulation model

Background

Greenhouse physics model:

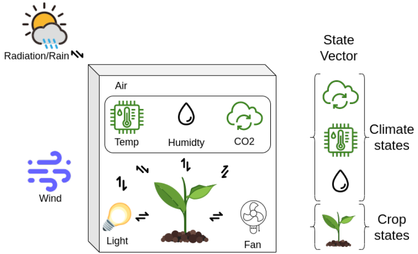

Figure: Example diagram of greenhouse physical processes

States in the greenhouse include:

- Include physical/biological quantities we want to predict and quantities that are needed to predict them.
- Climate states and crop states.
- Observable and unobservable states.

Background

Problem setting:
Given

- an initial state vector x_i
- a sequence of T control vector $u_i, u_{i+1}, ..., u_{i+T-1}$
- each control vector is for a fixed time interval Δt

Task: Find the simulation model, parameterized by θ, denoted $\mathcal{S}_\theta$, which predicts the next state vector from the current state and control vector $\hat{x}_{t+1} = \mathcal{S}(x_t, u_t)$ such that it minimizes the prediction error of the next T state vectors $\hat{x}_{i+1}, \hat{x}_{i+2}, ..., \hat{x}_{i+T}$.

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Physics-based greenhouse simulation

The physics follows a system of linear differential equations:

$$\dot{x} = A_\theta(x, u)x + b_\theta(x, u) \quad (1)$$

The simulation model consists of two step:

- Construct the matrix $A_\theta(x_t, u_t)$ and the vector $b_\theta(x_t, u_t)$ using the current physical parameter vector θ, the state vector x_t, and the control vector u_t.
- Solve the linear system of linear differential equation to obtain the next state vector prediction $\hat{x}_{t+1}$.

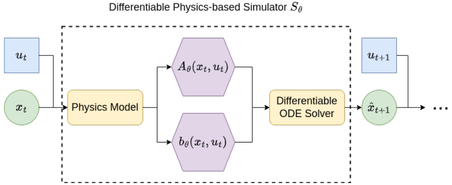

Figure: Diagram of the physics-based simulation model

Physics-based greenhouse simulation

- To construct the matrix and vector for the linear differential equation, we base our model on prior works ([1], [2]).
- The system of linear differential equation has a closed form solution using matrix exponential:

$$x(t+h) = e^{hA}x(t) + \left(\int_0^h e^{\tau A} d\tau\right) b \quad (2)$$

  The second term can be computed stably by converting it to matrix exponential form.
- Compute the matrix exponentials using Taylor expansion:

$$e^X = \sum_{j=0}^{\infty} \frac{(X)^j}{j!} = \sum_{j=0}^{\infty} C_j \text{ where } C_j = \frac{1}{j} \times C_{j-1} \times X \text{ for } j > 0 \text{ and } C_0 = 1 \quad (3)$$

- Everything are implemented in Pytorch.

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Dataset and training losses

Dataset: Autonomous Greenhouse 2018 dataset.

- Has information on greenhouse climate, irrigation, outdoor weather, control setpoints, crop management, and resource consumption.
- Tens of thousands of data point with timestep $\Delta t = 5$ minutes.

Supervised learning problem. Separate training for climate states loss and crop states loss:

- Climate: Air temperature, vapor pressure, CO2

$$\mathcal{L}_1(\theta, i) = \frac{1}{T} \sum_{k=i+1}^{i+T} \left[\omega^{Temp} (\hat{\boldsymbol{x}}_k^{Temp} - \boldsymbol{x}_k^{Temp})^2 + \omega^{VP} (\hat{\boldsymbol{x}}_k^{VP} - \boldsymbol{x}_k^{VP})^2 + \omega^{CO2} (\hat{\boldsymbol{x}}_k^{CO2} - \boldsymbol{x}_k^{CO2})^2 \right]$$

- Crop: cumulative harvested fruit weight and fruit count

$$\mathcal{L}_2(\theta, i) = \sum_{k} \left[\omega^{HW} (\hat{\boldsymbol{x}}_k^{HW} - \boldsymbol{x}_k^{HW})^2 + \omega^{HC} (\hat{\boldsymbol{x}}_k^{HC} - \boldsymbol{x}_k^{HC})^2 \right]$$

Results

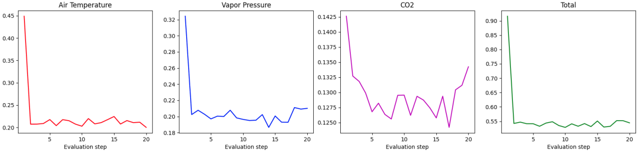
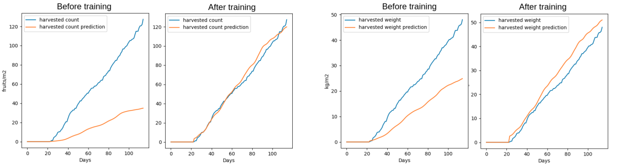


Figure: Individual loss components and total loss of the climate states on Croperator dataset.



(a) Comparison of cumulative harvested fruit number before and after training

(b) Comparison of cumulative harvested fruit weight before and after training

Figure: Crop prediction performance before and after training on the Croperators. Blue: Ground truth. Orange: Our physics-based simulator prediction. Left: Cumulative harvested fruit number. Right: Cumulative harvested fruit weight.

Conclusions

- We presented an interpretable and differentiable physics-based greenhouse simulation model and proposed an efficient inference and training procedure for it.
- Future work include more rigorous experiments, experimenting with more crop types, and to exploit the fact that the crop dynamics changes slower than the climate dynamics to improve speed.

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