Data-Drven Control for Societal-Scale **Cyber-Physical Systems**

Yuanyuan Shi and Baosen Zhang

Introduction

Decisions on how to best operate societal-scale cyberphysical systems (CPS) such as energy systems, transportation networks and robotics are becoming increasingly challenging because of the growing system complexity and environmental uncertainties. Recent years, with the explosion of data and rapid development of machine learning algorithms, data-driven control shows promise for addressing the aforementioned challenges.



My research explores the theoretical foundations and applications of data-driven control from two perspectives:

- How can we design data-driven control algorithms for complex physical systems?
- How we analyze the interactions between multiple intelligent agents and design better platform?

About Me

Yuanyuan Shi is a fifth-year Ph.D. candidate at the ECE department. She works in energy systems and cyberphysical systems, from the perspectives of machine learning, optimization and control. Contact: yyshi@uw.edu

Electrical & Computer Engineering, University of Washington



Learn System Dynamics

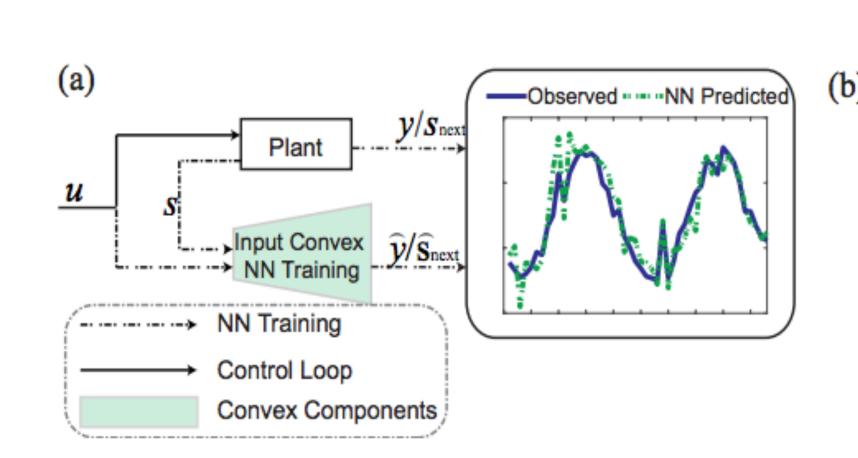


Figure 1: Model predictive control flowchart. (a) system identification (b) controller design

- We designed an **input convex neural network** (ICNN) [1] for complex system identification, where all weights of ICNN are nonnegative, adding pass-through layers and use ReLU activations.
- ICNN can represent all convex functions
- ICNN is exponentially more efficient than piece-wise linear model
- Used in building energy management, robotics control and power system voltage regulation

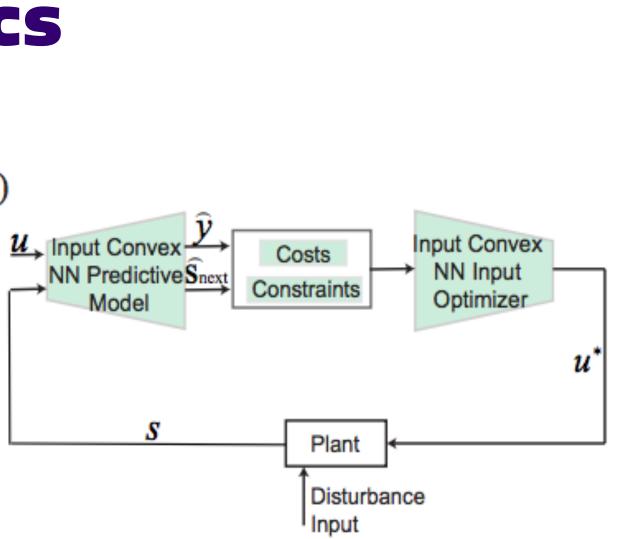
End-to-End Learning under Uncertainty

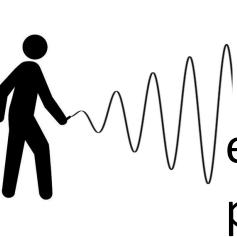
The operation of CPS often encompass a myriad of uncertainties that come from external environment and human behavior. Most previous stochastic online controllers uses a **two-step** framework: 1) predict the uncertainties; 2) solve the optimization using the prediction, which leads to error accumulation and sub-optimality.

Features Historical sales, lead time, ...



Optimize: Optimal replenishment quantity





error propagation

- and robotics control [4]

Interaction of multiple intelligent agents



Question 1: Will system still stable or can be manipulated [5]?

• Learning agents (e.g., no-regret learning, policy gradient reinforcement learning) will converge to the Nash Equilibrium Convergence speeds depends on the algorithms of usage Question 2: How to design better mechanism (information, price) for societal-scale CPS?

Reference

[1] Chen, Y.*, Shi, Y.*, & Zhang, B., Optimal Control Via Neural Networks: A Convex Approach (*equal contribution). International Conference on Learning Representations (ICLR), 2019. [2] Shi, Y., Qi, M., Ma, C.X., Yuan R., Wu D., & Shen Z. M., "A practical end-to-end inventory management model with deep learning," under revision in *Management Science*, 2019. [3] Shi, Y., Xu, B., Tan, Y., Kirschen, D., & Zhang, B., Optimal Battery Control Under Cycle Aging Mechanisms in Pay for Performance Settings. *IEEE Transactions on Automatic Control,* 2018. [4] Shi, Y., Xiao, K., Mankowitz D. and et al Data-Driven Robust Reinforcement Learning for Continuous Control. NeurIPS Workshop on Safety and Robustness in Decision Making (NeurIPS), 2019. [5] Shi, Y., & Zhang, B., Learning in Cournot Games with Limited Information Feedback. *arXiv preprint* arXiv:1906.06612, 2019

We designed an end-to-end modular neural network for

stochastic control problem that have multiple sources of uncertainties and no simple closed-form solution

Get the label for each sample by solving dynamic programming Used for inventory management [2], energy storage control [3],

- Energy market example
- Generators bid in quantity
- Every player is self-interest (profit maximization) and smart (learning algorithm)