PERFECTING OPTICAL FIBERS

MIT DEVICE REALIZATION LAB

STERLITE

DEEP REINFORCEMENT LEARNING FOR PREDICTIVE CONTROL

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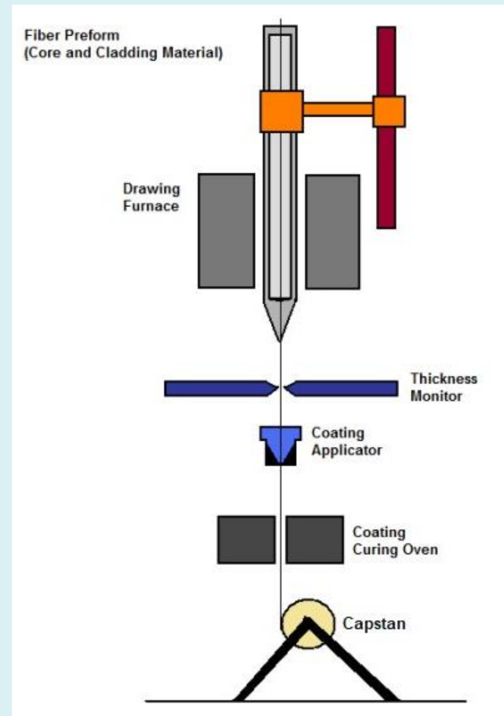
PROBLEM OVERVIEW

PROBLEM CONTEXT

OPTICAL FIBERS

The Backbone of Modern Global Connectivity

- Thin, flexible strands of glass
- Transmit data through light pulses
- Based on Total Internal Reflection



Optical Fiber Manufacturing Process

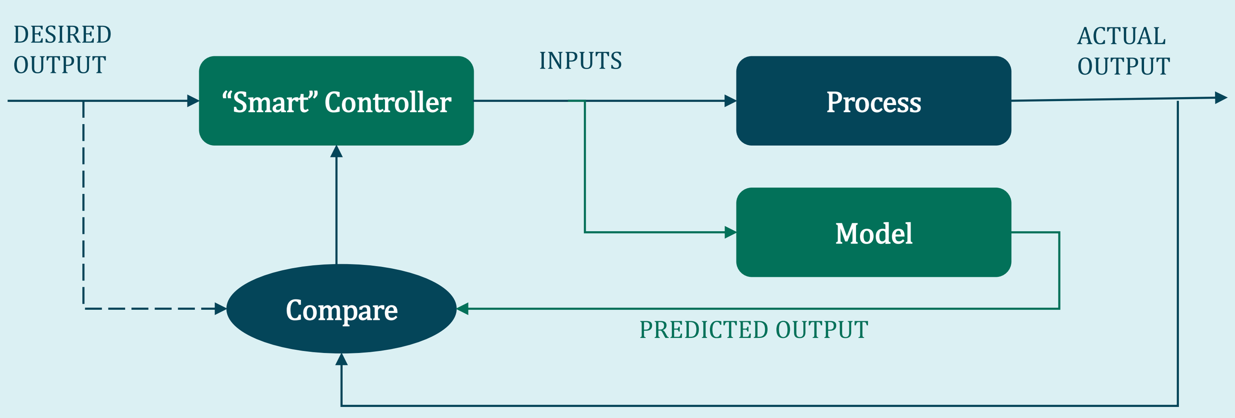
Fiber Extrusion Setup

Pre-processed glass rod (preform) » Furnace » Hair-thin fibers

Industrial Controller

Automates manufacturing process by regulating physical inputs (power/ temperature/ speed) to achieve desired output properties

The controller at Sterlite compares the true output diameter with the desired diameter and then controls the inputs accordingly



Problem at Sterlite: Inefficient Control

Current solution is unable to maintain the fiber diameter within the specified range (125±0.1 microns)

Required Solution: Smart Controller capable of predicting outputs and taking pre-emptive actions

BUSINESS IMPACT

Monthly Wastage

100 meters — Raw Material

7% — Production Time

$1.5M — Final Product

Target: Maintain Fiber Diameter within 125±0.1 microns

PROBLEM BREAKDOWN

Problem: Raw Material **Wastage**
Solution: Develop a **Predictive Model** of the process for understanding input-output relationship

Problem: **Sub-optimal Hyperparameter** Settings
Solution: **Optimize** controller settings based on model predictions in the simulator

Problem: **Inefficient Controller** Architecture
Solution: Build an alternate **Pre-emptive Controller** that incorporates the predictive component and takes anticipatory actions

DATA

DATA DESCRIPTION

Data sampled every ~100ms → High Frequency Time-Series

500K Daily Datapoints

8 Features of Interest

2 Targets

INPUTS (FEATURES)

- Preform Speed
- Furnace Power
- Helium Tube Temperature
- Capstan Slope
- Capstan Speed
- Radial Position
- Preform Diameter

OUTPUTS (TARGET)

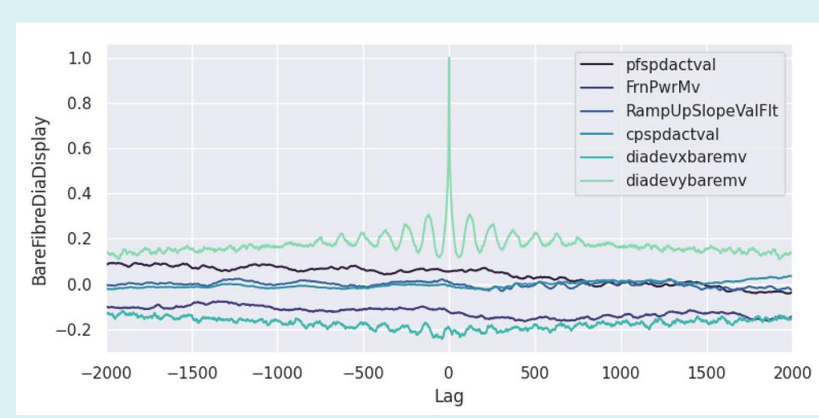
- Fiber Diameter
- Fiber Tension

PREPROCESSING

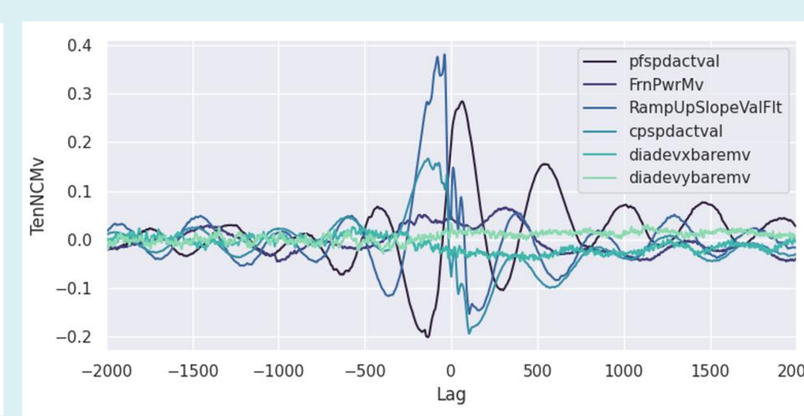
1. Batching
2. Interpolation
3. Filtering
4. Sanitization
5. Smoothing

ANALYSIS

Cross-Correlations of Inputs with Diameter



Cross-Correlations of Inputs with Tension



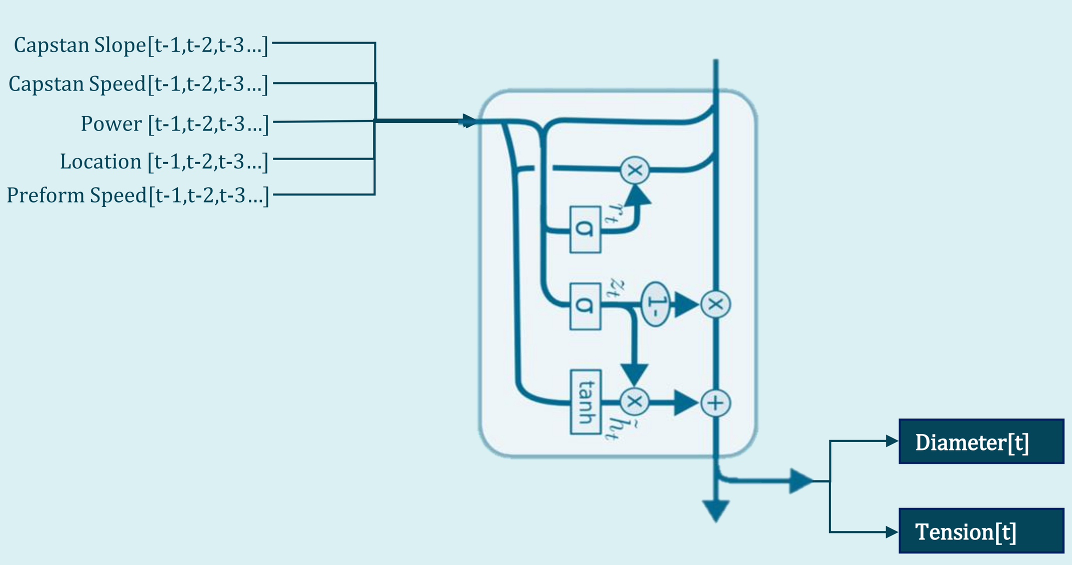
Relationship exists until a look-back of 50 time-steps

METHODOLOGY & RESULTS

PREDICTIVE MODELING – SEQUENTIAL LSTM

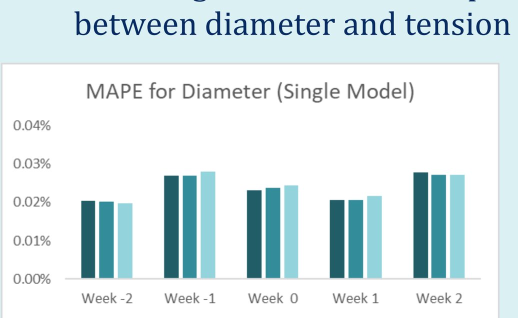
Problem: Traditional models (ARIMA, Exponential Smoothing, Prophet) only capture linear and stationary relationships

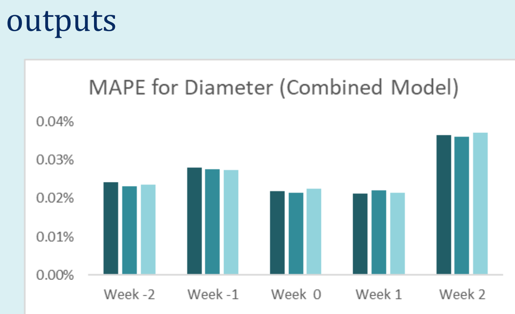
Solution: Use Deep Learning-based sequential models (LSTM)



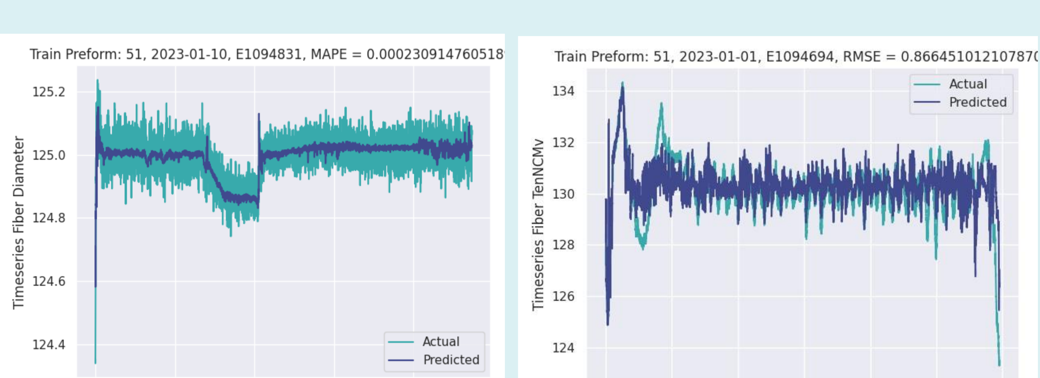
LSTM Experiments:

- Architecture Choice: Vanilla Model is fast and has fewer parameters without compromising on performance
- Modeling Choice: Multi-Output Model captures interdependencies between diameter and tension outputs





The **Multi-Output Vanilla LSTM** model accurately captures diameter trends, achieving a mean absolute percentage error of **0.01%** for diameter and **1%** for tension trends ☺



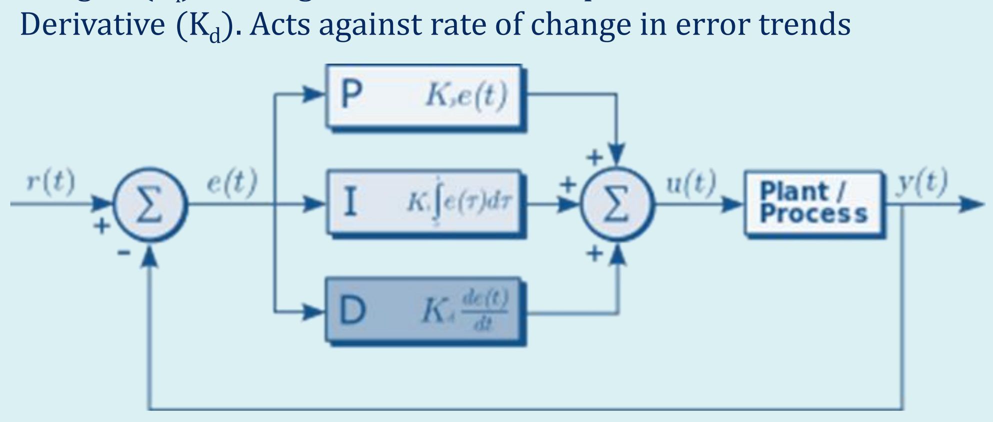
PARAMETER OPTIMIZATION – ZIEGLER NICHOLS HEURISTIC

PID Controller

Feedback control algorithm to regulate systems to reach desired setpoints

3 Hyperparameters:

- Proportional (K_p): Acts against current error
- Integral (K_i): Acts against accumulated past errors
- Derivative (K_d). Acts against rate of change in error trends



Controller Equation: $u(t) = K_p e(t) + K_i \int e(t) d(t) + K_d \frac{de}{dt}$

Existing Controller Network at Sterlite Controls 3 Variables

1. Preform Velocity Controller: Feedback from Diameter (125 microns)
2. Capstan Velocity Controller: Feedback from Diameter (125 microns)
3. Furnace Power: Feedback from Tension (130 units)

Problem: Huge Search Space

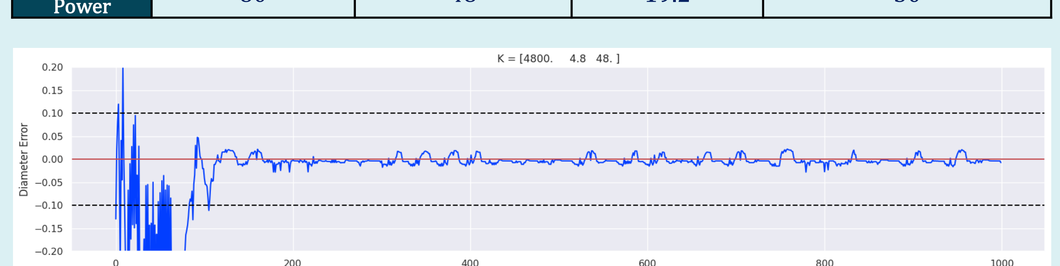
3 PID Controllers x 3 continuous parameters

Solution: Ziegler-Nichols Heuristic

Chooses ideal PID parameters, without navigating entire search space

Environment: LSTM model used to simulate the manufacturing process

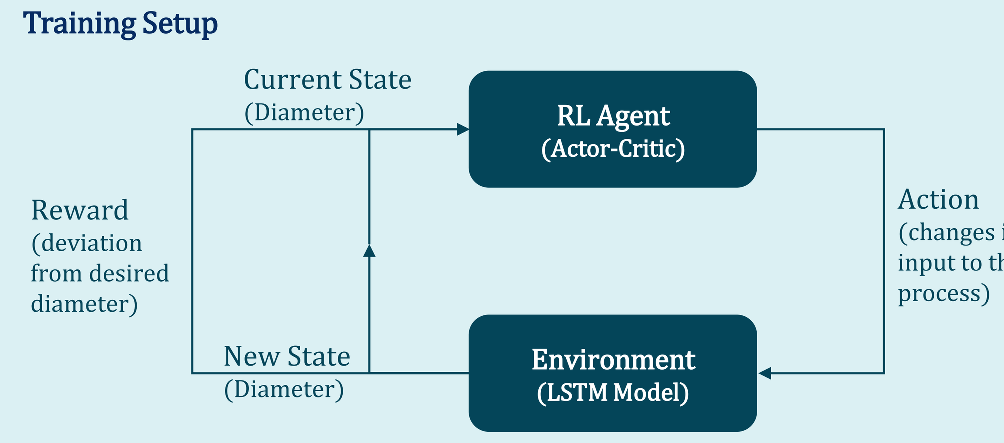
Controller	$K_{p_{cr}}$ ($P_{cr} = 5$)	$K_p = 0.6 * K_{p_{cr}}$	$K_i = \frac{2 * K_p}{P_{cr}}$	$K_d = 0.125 * K_p * P_{cr}$
Capstan Velocity	8000	4800	1920	3000
Preform Velocity	8	4.8	1.92	3
Furnace Power	80	48	19.2	30



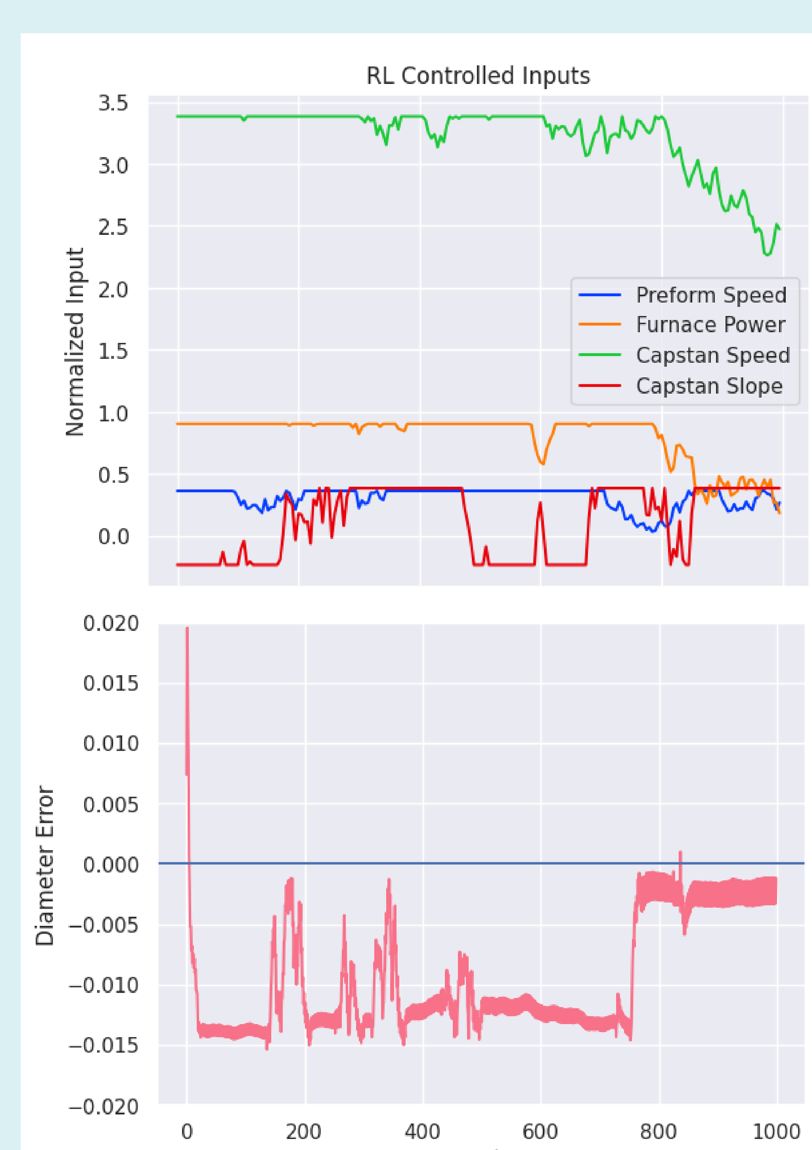
Although simulation outputs are within bounds, the controlled inputs are frequently out of range and violate physics-based constraints and as a result, the **parameters are unusable** ☹

ALTERNATE CONTROL SYSTEM – REINFORCEMENT LEARNING

Training Setup



- **Problem:** Traditional PID Controller suffers from Linearity Assumptions
- **Solution:** Reinforcement Learning Controller:
  - ✓ Reward settles to a value close to zero as the model converges
  - ✓ All inputs stay within bounds and follow physics-based constraints
  - ✓ **Control (Diameter) Error stays within 0.01 microns (10x better)** ☺



IMPACT AND FUTURE WORK

CONCLUSION

Built a cutting-edge solution to improve **Optical Fiber Manufacturing Process** utilizing a combination of **Long Short-Term Memory (LSTM) Modeling** and **Reinforcement Learning (RL)**

Maintained fiber diameter within an incredibly tight range of **125 ± 0.1 microns** on test simulations, providing **potential savings of $1.5 million/month**

FUTURE WORK

- ❑ Make the LSTM model more robust by training and re-training across multiple weeks
- ❑ Improve identified PID parameters and explore alternate heuristics for optimization
- ❑ Thoroughly test the RL-based control system on the physical manufacturing units