Project 1: Switching Regime-Sensitive Model Predictive Controller (MPC) for Portfolio or Risky Process Management – LNR, Ayush, Deepak & Raghav

Goal:

Design a simulated control system (e.g., financial portfolio allocation, chemical process, energy management) subject to hidden regime switches (detected by HMMs/Markov-switching models) and regime-dependent uncertainty (modeled with GARCH). Implement an MPC framework that dynamically adapts actions based on regime and time-varying uncertainty.

Key Steps:

1. **Simulate Process:** Generate a process where mean, variance, and constraint bounds change with hidden regime, using a Markov chain.
2. **Regime Detection:** Use HMMs (Viterbi/Baum-Welch) to process outputs and estimate regime switches.
3. **Volatility Modeling:** Implement GARCH for regime-dependent prediction of stream variance.
4. **Regime-aware MPC:** At each step, use regime & volatility estimation for real-time MPC optimization—constraints and cost functions adapt to regime and uncertainty.
5. **Evaluation:** Compare regime-aware controller with naive/static ones for risk, returns, constraint violations.

Advanced Concepts:

- Probabilistic (chance) constraints in MPC
- Adaptive control with regime switching
- Volatility modeling via GARCH

References:

- https://en.wikipedia.org/wiki/Model_predictive_control
- Stanford Stochastic MPC Slides (PDF)
- Rawlings & Mayne: Model Predictive Control: Theory, Computation, and Design (textbook)
- GARCH 101: PDF Tutorial by Robert Engle
- ARCH/GARCH Python Notebook
- QuantStart GARCH Tutorial

Benchmarkable Datasets:

- Yahoo Finance Stock Data (S&P 500, ETFs)
- FRED Economic Time Series
- UCI Household Power Consumption

Project 2: Energy Demand Forecasting and Demand Response Control with Hybrid ML-Statistical Models – Hafiz, Sreekar & Nihal

Goal:
Simulate energy demand profiles with weather-driven regime switches. Use a hybrid HMM–ARIMA/LSTM/GARCH approach for demand forecasting under uncertainty, and optimize energy purchase/storage using these predictions in a rolling model predictive control framework.

Key Steps:

1. **Simulate/Obtain Energy Demand Data:** Use public data (see below) or synthetically generate demand with weather and regime dependence.
2. **Regime-Switching Forecaster:**
   - HMM for regime detection.
   - ARIMA/GARCH for simple regimes; LSTM for nonlinear/difficult regimes.
   - Combine regime posteriors for hybrid predicted demand & volatility.
3. **Rolling Horizon Control:**
   - At each time step, optimize energy purchase/storage for next day based on predicted demand and forecast uncertainty.
   - Dynamic constraints (cost, storage limits).
4. **Scenario Testing:**
   - Simulate system under weather changes, anomalies, and demand spikes.
   - Evaluate against baseline control (e.g., rolling average forecaster).

Advanced Concepts:

- Hybrid ML/statistical forecasting

- Robust/uncertainty-aware model predictive control
- Multi-step scenario simulation

References:

- https://web-static.stern.nyu.edu/rengle/GARCH101.PDF
- https://arxiv.org/abs/2307.04954
- Hong et al: Load Forecasting Hybrid Models (PLOS ONE)
- Australian Energy Market Operator Data
- NOAA Weather Data