System Identification Technques

SPA DRP Aut 2024

Mentor: Yash Talwekar

Mentee: Yash Anand

This quarter, I learned about system identification techniques, which involve creating mathematical models to describe and predict the behavior of dynamic systems based on precious/ observed input and output data. I learned about the key concepts behind system identification, the challenges it addresses, and the mathematical methods used to estimate system parameters. Combining these insights, I applied system identification techniques to analyze and model a spring mass damper system, a basic example in engineering that demonstrates dynamic interactions between force and motion. Through this project, I gained a lot of experience in identifying system parameters and evaluating model accuracy using real-world data.

System identification helps to understand how systems behave under arbitrary input and thus enables better prediction and optimization. For example, if we take a spring mass damper; while the forces acting in such a system are spring force, damping force, and force of inertia, the displacing quantity is associated with spring force, the corresponding damping velocity, and inertial force to acceleration. These three forces can be related to each other with an appropriate mathematical equation to model the system. Parameters such as the spring constant or the damping coefficient can only be determined by combining observed data with optimization techniques.

One of the main methods I used was the Auto-Regressive model with Exogenous Input (ARX). The model estimates system parameters by analyzing past outputs and current inputs to predict future outputs. The process involved defining a mathematical structure for the system, collecting input and output data, and solving for coefficients that minimize prediction error. For example, in the spring mass damper system, parameters such as a_1, a_2, and b_1 represent how past outputs and inputs influence the current output. By fitting these coefficients using techniques like the Moore-Penrose pseudo-inverse, I was able to derive an accurate representation of the system.

Another critical aspect of the project was evaluating and generalizing the model. To verify the accuracy, I calculated the Mean Squared Error (MSE), a formula that quantifies how well the model predicts the observed data. Additionally, I extended the model structure by including more coefficients to account for complex systems that require deeper historical data to make accurate predictions. This generalization was necessary for handling systems with intricate dynamics, but it also highlighted the challenge of overfitting. Overfitting occurs when a model becomes too complex, fitting noise in the training data rather than capturing the true system behavior. As a result, the model performs poorly on new data, emphasizing the importance of balancing complexity and generalization.

Through this project, I learned not only the theoretical foundations of system identification but also its practical challenges and limitations. The application of ARX models and the exploration of generalized structures provided valuable insights into how dynamic systems can be modeled effectively. From this experience, I understood the importance of rigorous evaluation and the pros and cons involved in designing models that are both accurate and robust. Overall, this quarter's work gave me a deeper appreciation for the power of mathematical modeling in understanding and optimizing complex systems.