FAU Friedrich-Alexander-Universität Naturwissenschaftliche Fakultät

DDS Department of DATA SCIENCE

Fraunhofer IIS

Master's thesis:

Stochastic Inventory Planning and Machine Learning-based Policy Approximation in Multi-Echelon Supply Chains

Background

In contemporary supply chains, managing inventory across multiple stages—ranging from raw material procurement to final assembly—requires sophisticated coordination under uncertainty. Demand for end-products fluctuates over time and is inherently uncertain, while lead times for production and procurement are deterministic yet potentially long and variable across nodes. Inefficiencies such as misaligned material availability and unbalanced inventory levels can result in high holding costs or unsatisfied customer demand, each with associated financial penalties.

Thesis Objectives

The overarching goal of this thesis is to design and evaluate an effective inventory planning policy for a multi-echelon supply chain under stochastic demand. The specific objectives include:

Modeling

- Formulate the inventory planning problem as a multistage stochastic optimization problem with integer decision variables.
- Represent customer demand given as an autoregressive (AR) process with stochastic disaggregation among end-products.

Solution via Stochastic Programming

- Leverage the structure of the problem to apply Stochastic Dual Dynamic Programming (SDDP) under the assumption that stage-wise uncertainties can be modeled as independent.
- Investigate the scalability and performance limits of SDDP when applied to large-horizon instances.

Fast Evaluation via Learning-Based Policy Approximation

- Develop a data-driven approximation of the optimal policy by solving numerous stochastic instances to generate labeled data.
- Train a supervised machine learning model (e.g., decision trees, neural networks, or gradient boosting models) that mimics optimal decisions and enables fast policy evaluation.
- Benchmark the trained model's performance against both the true optimal and naïve baseline policies.

Expected Contributions

- A structured multistage stochastic programming formulation of the inventory control problem.
- An implementation of SDDP tailored to the problem structure, including custom stage modeling and value function approximations.
- A novel pipeline for policy learning using simulation-optimization data.

Candidate Background

- Strong background in operations research or applied mathematics.
- Solid programming skills (Python preferred)
- Familiarity with stochastic optimization, integer programming, and basic machine learning methods.
- Interest in bridging theory with computational methods.

This thesis will be supervised jointly by the the Department of Data Science (Frauke Liers) and the Fraunhofer IIS Group Optimization (Simon Hölck, Martina Kuchlbauer, Tobias Kuen).

Contact

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In case of interest please send an email including a Transcript of Records, a short Letter of Motivation as well as a preferred starting date.

References

[1] Christian Füllner and Steffen Rebennack. Stochastic dual dynamic programming and its variants – a review. https://optimization-online.org/2021/01/8217/, January 2021. Preprint, Karlsruhe Institute of Technology.

[2] ISIR 2025 Committee and ASML. Asml production-inventory planning research challenge. https://www.isir2025.com/research-challenge/information, 2025. Research challenge organized in collaboration with ASML.