How AI and Data Science can Contribute to Supply Chain Resilience

Henning Blunck, Deutsche Post DHL Group

In this talk, I want to outline how a traditional, sequential approach to demand sensing and subsequent supply chain optimization yields brittle, insufficiently robust design decisions and how the two steps can be integrated to design and plan for uncertainty.

Status Quo: Separation of Forecasting and Design/Planning

Forecasting demand on nodes or edges in the supply chain has been one of the most widely explored fields of application of data science in the domain of supply chain management. Applying methods of machine learning to sense and extrapolate demand signals in historic data, the hope is to automate the (so far often manual) task of demand prediction while incorporating the effect of external features (like holidays, sales events, …) that largely go beyond the capabilities of classical, time-series forecasting methods. No matter the applied methodology: Any demand forecast is probabilistic in nature. As the "first of rule forecasting" states: Every forecast is wrong!

The financial and operational benefits of improved demand forecasts stem from the (assumed) improvement in planning decisions that base on more accurate predictions of demand. Finding the optimal course of action, given anticipated demand patterns has largely fallen to deterministic models of (Mixed-Integer) Linear Programming (MIP/LP). **In their conventional setup, these models assume inputs (like forecasted demands) to be deterministic, thus creating a brittle, over-optimized solution that is not designed to absorb changes in environment conditions that were not part of the point forecast.**

Suggested Remedy #1: Robust Optimization across multiple demand scenarios

A first remedy for above-described problems can be achieved by applying some form of robust optimization, in particular scenario optimization. Instead of finding a set of decisions optimal for one (assumed to be deterministic) scenario, a set of scenarios perceived (more or less) likely is provided and the optimization model is tasked with finding a solution that is robust w.r.t. the incorporated uncertainty.

Scenario optimization is a well established tool that allows to explicitly model and account for uncertainty through scenarios with different probabilities and obtain solutions robust in the sense that they minimize either e.g. the expected cost or the worst case cost.

However, classical scenario optimization spends little thought on which scenarios should be used and which probability should be assigned to them. Often using random samples of scenarios that are 1) not necessarily representative of the future and 2.) assume an unnecessarily high degree of uncertainty.

Suggested Remedy #2: Let the ML model suggest the scenarios: Prescriptive Optimization

Prescriptive optimization is a rather new field of research that tries to combine methods of machine learning and mathematical optimization. It can be though of as using a machine learning model to generate scenarios for scenario optimization. This combination of methods allows to employ machine learning models to first reduce uncertainty (without ignoring the remaining one) and then deploying methods of scenario optimization of find a robust solution given these scenarios.

Short Bio: Henning Blunck

Henning studied industrial engineering at Dortmund University of Technology from 2006 to 2012, obtaining a Diploma (Master's equivalent) in Logistics. In 2010/2011 he also obtained a Master's degree in Industrial Engineering from the Georgia Institute of Technology. From 2012 till 2017 he worked as a Research Associate and PhD Student at Jacobs University Bremen (Germany) in the group of Prof. Arlinghaus. His PhD Thesis is titled "Designing Manufacturing Systems for Distributed Control". In 2017 he joined Deutsche Post DHL Group as a Data Scientist in the Central Data Analytics Center of Excellence where he today works as a the team lead for a team of 12 Operations Research Scientists.