A Generalized Framework for Optimization with Risk

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Summary: Supply chains are facing increasingly volatile environments. Traditional optimization solutions provide a baseline understanding for industry applications, but cost-efficient solutions require a more robust approach. In high-tech capital construction projects, the construction of facilities requires complex project schedules, forecast well in advance. These forecasts are used to hire contract workers of varying contract lengths. In this thesis, we develop a risk integration methodology for contract workforce hiring optimization, and explore the capability of generalizing this approach for other supply chain problems. In the studied case, a 23% additional risk coverage was generated for equivalent cost.

Prior to attending MIT, Damaris graduated with a Bachelor of Science in Operations & Supply Chain Management from the Georgia Institute of Technology. She has worked for Intel, IBM, and Bush Brothers & Co. in Strategy, Advanced Analytics, and Supply Chain roles. Upon graduation, Damaris will join Amazon as a Senior Manager in RLD in Seattle, WA.

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KEY INSIGHTS

1. Strategic risk-integrated optimization can result in significant cost savings and better risk coverage than traditional optimization methods.
2. If a thorough risk assessment is performed to understand the underlying risk parameters in the data, simulation is a strong method for identifying areas of high risk density in supply chain problems.
3. There is a maximum efficient point of coverage, to which a static optimal solution has an equivalent cost. Additional coverage beyond this point will cause the company to experience steep diminishing returns.

Introduction

Supply chains across all industries are currently plagued with a problem: is there a robust method to optimize operations by taking risk into account? In this thesis, we explore a methodology for solving one specific supply chain issue for our sponsor company, Intel. This methodology is then extracted into a general framework that integrates risk into optimization.

High-tech capital construction projects require complex project schedules. These schedules are forecasted well in advance, and labor requirements are derived from them. The required labor must be contracted and trained for lengthy periods of time before construction and installation begins. Due to the uncertain nature of project schedules, labor optimization must include consideration of project variance, or risk. The problem we address in this thesis is optimizing resource allocation across forecasted construction schedules, with consideration of schedule variance. We also address the constraints of contract labor duration, varying task types, and sequential ordering of tasks.

Traditional Optimization Methods

Traditional optimization methods create a solution for the current, static case, ignoring risk and variance. Often, these solutions result in higher final costs due to underutilized long-term contracts and expensive replacement workers.

Methodology Overview

To address the shortcomings of traditional deterministic methods, we created two methods of risk integration (a bottom-up and a top-down approach) via a simulation model. The first step in simulation was to determine what parameters involved risk (i.e. those that could change), and to measure their underlying risk distributions. We then worked to understand the risk density and risk coverage achieved by the initial optimal solutions output from the simulation. Each of the risk integration methods created a new set of headcount requirements over which to optimize. These new requirements strategically positioned additional headcounts on the schedule to exploit longer contracts. The costs and coverages achieved were then benchmarked against those provided by traditional solutions.

Risk Parameters Assessment

To develop a simulation model, we first needed a probabilistic understanding of the business context. More specifically, we needed the:

- Probability that individual task types would change location on the schedule
- Probability of movement forward or backward on the schedule
- Distribution of the magnitudes of these task moves
- Input of the assumed most recent forecast schedule

Simulation

In the provided data sets, scheduled tasks were uniquely defined by the combination of work unit and type. Under each work unit, tasks were assumed to be sequential, with a potential tension (n) measurement between the two, and with one task type assumed to be independent. With these restrictions, we created a model to simulate possible versions of the final production schedule.

This simulation was designed to perform eight main tasks:

1. Import and analyze data
2. Simulate different possible schedules
3. Optimize each of the simulated schedules
4. Assign risk coverage values to each optimal solution
5. Understand the resulting statistics around risk coverage
6. Weigh the risk coverage impact of changing the headcount requirements
7. Assign new headcount requirements by day based on several desired coverage percentages, optimizing the results to take advantage of longer term contracts
8. Output the optimized sets as a portfolio of options

Mixed Integer Optimization Model

To create a base optimization case for the provided schedules, we built a mixed integer programming model. This model output results where we could compare statically optimal solutions based on each schedule iteration, as well as modify constraints in order to compare different scenarios. The model contained known inputs, constraints, decision variables, and an objective function. Figure 1 illustrates one result from this model.

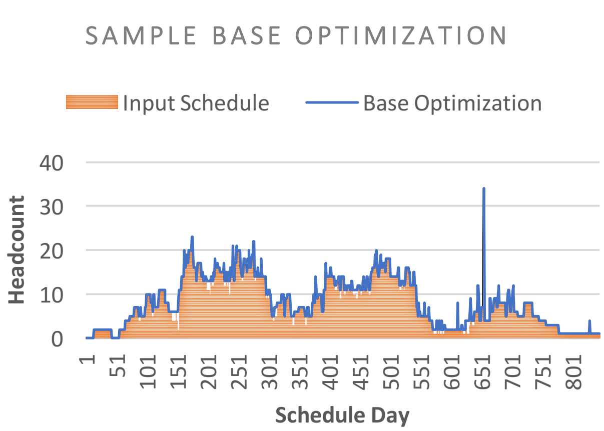

Figure 1. Base Optimization Overlaid on Input Schedule

Coverage Assessment

Once the schedules were iterated from the input schedule and optimized with the mixed integer optimization model, we developed the risk integration component. The optimized schedules were run against a set coverage solution to determine the deficiencies experienced by day, and their predicted coverage of the final schedule.

Then, we calculated the average deficiencies and standard deviations of deficiency experience by schedule, by day. These statistics helped us to understand which areas in the schedule experience higher variability, and thus would benefit most from strategic handling during optimization.

Risk Integration Methods

The goal of the two risk integration methods developed was ultimately to re-build the base requirements in order to better exploit the optimization engine's capabilities in establishing long-term contracts and better risk set coverage in a cost-effective manner.

Method 1 – Handling Risk from the Bottom-up

The first method we used addressed risk integration at a daily level. For each day, a z-score was calculated for each desired risk coverage by determining the necessary probability value of additional coverage as follows:

Prob=(DesiredCoverage-BaseCov)/(100%-BaseCov);
where BaseCov = coverage achieved by input schedule.

This z-score was applied to determine an additional headcount for each day, for each desired coverage. The final equation for the new head count requirements by day is as follows:

NewHCReq_i = z*AvgDefStDev_i + AvgDefAvg_i +BaseSched_i.

Method 2 – Handling Risk from the Top-Down

The second method we used addressed risk integration at a schedule-wide level. To address the integration of risk coverage on a schedule-wide level, we first had to assess the coverage achieved by the base schedule on its own. In this case, we took the input schedule as our base. This coverage was determined by comparing the input schedule to the maximum requirements schedule. This coverage typically averaged ~55-62%.

Then, the gap between the desired coverage, y, and the base coverage, x, was determined. This gap was taken as a percentage of the desired coverage:

Gap Percentage=(y-x)/y

Once the gap was determined, we retrieved the list of average deficiencies by day that we calculated in the previous section. This gap percentage was used to determine the percentile value to utilize across list of daily average deficiencies.

Cost-Coverage Frontier

The natural result of covering more risk is to incur additional upfront cost, with the expectation of incurring less overall cost. Thus, the natural output of this simulation program is a

Cost vs. Risk Coverage Frontier. Figure 2 is a visualization of the portfolio of options resulting from the simulation.

In the program, we determined the cost performance of the base optimization as well as that of the risk-integrated solutions provided by the simulation. These costs were calculated against the test data set's "actual" final schedule. In order to create a cost benchmark, we took the optimal cost as the base cost, and then added BOH coverage to any deficiency that the proposed schedule had against the actual final schedule. This extra cost was then added to the base price. Moreover, we calculated the actual coverage of each schedule against the final schedule.

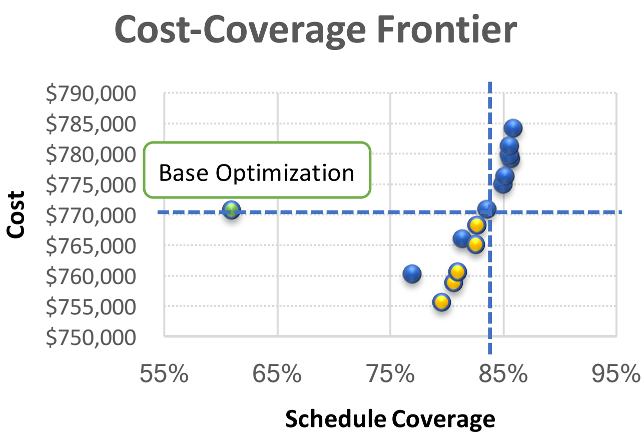

Figure 2. Cost Coverage Frontier Sample

Generalized Framework for Optimization with Risk

The methodology used in this thesis can be generalized and used in a variety of settings, as described in Figure 3. In diverse areas like manufacturing, customer experience, and distribution, our framework can be applied in to create risk-integrated solutions for real-world application.

Figure 3. Generalized Framework for Risk Optimization

Conclusion

Risk management is, without a doubt, a central issue in supply chains today. While optimization engines have become powerful enough to handle large problems, companies have found that deterministic solutions to organic problems are simply not enough. Using our methodology, we found that higher levels of risk coverage were achieved at lower costs than the traditional solutions. In the studied case, a 23% additional risk coverage was generated for equivalent cost. We created an efficiency frontier using two different methods for risk integration. Ultimately, the results show that strategic risk integration can result in a lower final cost, and a generalized framework for risk integration can be applied across many supply chain problems.