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Risk-aware procurement optimization in a global technology supply chain

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Risk-Aware Procurement Optimization in a Global Technology Supply Chain

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Abstract. Supply chain disruption, from 'Black Swan' events like the COVID-19 pandemic or the Russian invasion of Ukraine, to more ordinary issues such as labour disputes and adverse weather conditions, can result in delays, missed orders, and financial loss for companies that deliver products globally. Developing a risk-tolerant procurement strategy that anticipates the logistical problems incurred by disruption involves both accurate quantification of risk and cost-effective decision-making. We develop a supplier-focused risk evaluation metric that constrains a procurement optimization model for a global technology company. Our solution offers practical risk tolerance and cost-effectiveness, accounting for a range of constraints that realistically reflect the way the company's procurement planners operate.

Keywords: Supply chain · Risk analysis · Procurement optimization

1 Introduction

The COVID-19 pandemic has revealed vulnerabilities in global supply chains, creating supply, demand, and logistics challenges that required immediate action, forcing supply chain executives to re-chart their courses. Other recent headline-grabbing supply chain challenges include the blocking of the Suez Canal by the Ever Given, and the Russian invasion of Ukraine, a significant producer of the world's food supply. However, while these 'Black Swan' scenarios attract global attention, supply chains must also deal with more ordinary, but also more frequent disruptions, such as natural disasters, labour disputes, tax policy changes, and transport disruptions. Supply chain resilience is a company's ability to navigate unexpected supply chain disruptions with its existing capabilities. In other words, supply chain resilience is the ability to react to problems and recover from them without significant impact on operations and customer timelines. Most of the short-term tactics to mitigate disruption involve reallocating production lines to other products, re-balancing workforce, shutting down production, and finding alternative logistics models and suppliers. Large companies can employ dedicated teams to handle this workload, therefore in this paper, we develop a

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medium-term procurement optimization method to provide a risk-robust procurement strategy that reduces the burden on short-term emergency response teams. Since supply chain disruption data can be challenging to acquire from third-party vendors, with the impact of a disruption event being difficult to accurately quantify, we develop a risk evaluation metric that assigns a risk score to suppliers based on multiple risk categories that allows direct optimization without the need to generate disruption scenarios from inadequate data.

The contributions of this paper are as follows. First, we develop a supplier risk score metric from multiple sources, performing factor analysis to identify key risk factors that lead to supply chain disruption. Second, based on the risk scores, we formulate a risk-constrained optimization model that generates a parts procurement strategy for a global computer manufacturing firm. We then compare our optimization model against a baseline greedy approach, and evaluate the cost-effectiveness of our plan against historical procurement data obtained from the procurement department.

2 Literature Review

A critical review on supply chain risk has been conducted in [5], which reviewed existing approaches for quantitative supply chain risk management by setting the focus on the definition of supply chain risk and related concepts. An end-to-end supply chain risk management process (SCRMP) was proposed in [10] for managers to assess and manage risks in supply chains. The structured approach can be divided into the phases of risk identification, measurement, and assessment; risk evaluation; and mitigation and contingency plans. For supply chain risk assessment, [1] proposed a fuzzy-based integrated framework. It first identifies risks based on an expert's knowledge, historical data, and supply chain structure. Then the proposed fuzzy inference system is used to calculate the aggregated total risk score, considering the risk management parameters and risk predictability. [4] carried out a case study for supplier risk assessment based on expert rating and supplier clustering. 72 existing suppliers were evaluated and clustered into 3 different clusters, and each cluster had 17 risk criteria with scores to help decision makers select the best suppliers. A graph-based model is proposed in [9] to measure the structural redundancy for supply chain resilience. The approach focuses on the resilience of the supply chain network against disruptions. Critical supply chain components are identified and the percentage of plants disrupted is calculated in their real-world case. Recently, supply chain risk management (SCRM) with artificial intelligence is also emerging. [2] provided a comprehensive review of supply chain literature that addresses problems relevant to SCRM using approaches that fall within the AI spectrum.

Optimization methods have been applied to a range of supply chain and logistics problems, mitigating risk and accounting for uncertainty. The classic Newsvendor Problem [7] makes advance purchasing decisions in the face of demand uncertainty, while supply chain disruption can be addressed using a portfolio approach that uses multiple time periods to estimate the impact of delay on the delivery time of an order [8]. For problems where the impact of disruption can be accurately quantified, it is appropriate to employ stochastic optimization to account for uncertainty, typically solved deterministically for multiple generated scenarios [6]. However, where available data does not permit the accurate realization of scenarios to optimize on, methods that draw directly on risk to constrain the scope of optimization can be employed, either introducing risk minimization as a joint objective with cost minimization, or through risk as a constraint on a cost minimization problem [3]. It is this last case that is the most appropriate for the technology company use case in this work.

3 Problem Description

In this paper we consider a global technology company that supplies a wide range of computer products encompassing both software and hardware for both consumers and businesses. To provide hardware solutions, such as enterprise-level servers, parts are obtained from a range of third-party suppliers, and then assembled according to customer orders. Contracts are arranged with each supplier on a long-term basis, with part procurement decisions taken for the medium term (3–6 months). In the event of supply disruption, a dedicated team is responsible for meeting demand from any sources available, with the goal of this work being to generate a risk-aware medium term procurement plan that reduces the burden on the disruption-response team. Parts supplied to the company may belong to 'Alternative Parts Groups' (APGs), where member parts in the group may be substituted for each other based on similar technical specifications in order to satisfy demand. Suppliers may optinally specify minimum purchase levels and rebate schemes in their contracts, where exceeding a threshold quantity of eligible parts purchased triggers a percentage discount on purchased parts. Since suppliers may not charge identical prices for the parts in an APG, and have varying risk levels, an effective risk-tolerant procurement strategy should balance cost, rebates, and risk.

It can be challenging to quantify risk in the real world, as many methods, particularly those employing machine learning, require a large quantity of consistent and accurate data on past disruptions, which may be difficult or time-consuming to obtain. To overcome this challenge, we develop a risk-score metric for each supplier, identifying a range of risk categories and formulating a representative score. These scores provide input to our risk-constrained optimization model that recommends a procurement strategy which minimizes the net cost of meeting part demand while not exceeding a chosen risk tolerance.

4 Supplier Risk Analysis

In this section, we present our risk analysis model. The technology company has several important products that need to be evaluated for risk. Our goal is to develop an automated resiliency metric, which is represented by a risk score from 0 to 10 (low to high), for the suppliers that deliver parts critical to products where supply chain risk is an essential consideration. Supply risk is a multidimensional concept that encompasses various risk factors such as supplier failure, disruption/loss of a supplier, non-suitable essential parts, late deliveries, and disruption due to catastrophic events. We decompose the risk analysis into the following five steps, as depicted in Fig. 1: (1) examine which risk categories must be addressed for each product, as well as which risk criteria must be evaluated within each broad risk category; (2) based on the selected risk criteria, collect related data from both internal and external (third-party companies) sources for analysis; (3) reduce the dimensionality of selected risk criteria, focusing on the most important factors; (4) calculate the risk score for each supplier; and finally, (5) dynamically update the risk score calculation method with feedback from suppliers.

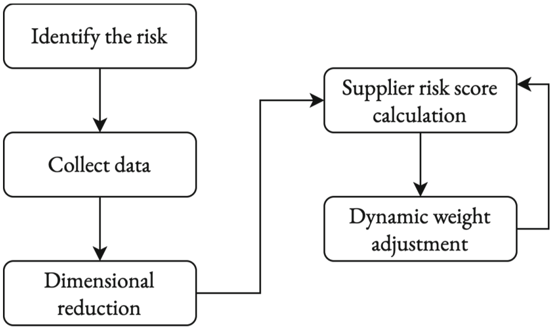


Fig. 1. Framework for risk analysis model

4.1 Risk Criteria Identification

First, we identify which criteria are appropriate for the risk assessment from the supplier perspective. Through literature review and detailed discussion with supply chain experts in our company, we produced a set of risk evaluation categories. The initial round of analysis identifies 12 different risk categories, such as socio-political, manufacturing, or financial, risks, which are then reduced to 6 in the second round of discussion. Finally, 13 risk criteria are chosen for further consideration in our supplier risk assessment.

4.2 Supplier Risk Score Calculation

Following the selection of risk criteria, the next step is to collect relevant data for each criterion from both internal and external third-party sources. The following data types were obtained from internal and external databases:

– Internal data: product information, market condition, supply business leverage data, financial data;

– External data: macroeconomic data (Economist database), socio-political data and rational data (e.g., geopolitical, legal), manufacturing and catastrophic data (Resilinc database);

Each of the criteria has a numerical value from 0 to 10 (after normalization) that represents the criterion's risk score (the higher the value, the greater the risk). Figure 2 shows an example of the data used to calculate the supply risk score. The first three columns contain supplier information, such as name, country, and city. The fourth column indicates whether or not the vendor is a subcontractor. The risk score data for selected criteria is contained in the remaining columns.

SUPPLIER	COUNTRY	CITY	SUBCONTRACTOR	CREDIT	RECOVERY	SOURCING	GEOPOLITICAL	MACROECONOMIC	RESILIENCY	...	POLITICAL
A	CHINA	ZHONGSHAN	0	1.00	1.00	8.00	6.00	3.00	3.00	...	5.00
B	CHINA	DONGGUAN	0	2.00	2.00	7.00	6.00	3.00	4.00	...	5.00
C	THAILAND	CHONBURI	0	5.00	1.00	6.00	6.00	4.00	4.00	...	6.00
D	CHINA	WUXI	1	3.00	10.00	9.00	6.00	3.00	6.00	...	5.00
E	SINGAPORE	SINGAPORE	0	0.00	5.00	9.00	6.00	3.00	5.00	...	2.00

Fig. 2. Sample of data collected for the calculation of supplier risk score

The final step in calculating supplier risk is to aggregate all of the risk score data into a single total. We utilize the weighted sum approach to determine the final risk score here because of the method's interpretability. We first introduce the notations for risk score calculation as follows:

– r_i: risk score for supplier i;
– w_i: weight assigned for criterion c_i;
– c_i: risk criterion i.

We then use a weighted sum to calculate the final risk score:

$$r_i = w_1 \cdot c_1 + w_2 \cdot c_2 + \cdots + w_n \cdot c_n \tag{1}$$

There may be a strong inter-correlation between each risk criterion, and the risk data with 19 criteria is too large and difficult to understand and manage. Hence we use a factor analysis to examine the relationships between these criteria and group them into a small number of factors, which is a common data dimension reduction technique. Factor analysis also allows us to discover intrinsic links and better comprehend the data.

4.3 Factor Analysis

In this part, we take the product anonymized as "A0001" in our company, which is a high-performance computer, as an example, and examine the correlation between different risk criteria using the risk data obtained. Figure 3 depicts the relationship between various risk criteria. The correlation coefficient ranges from

−1 to +1, and the closer the value is to +1, the higher is the positive linear relationship between the variables. It can be seen, for example, that the corruption perception index has high correlations with other risk criteria, such as infrastructure risk, labour market risk, tax policy risk, financial risk, foreign trade, payments risk and so on.

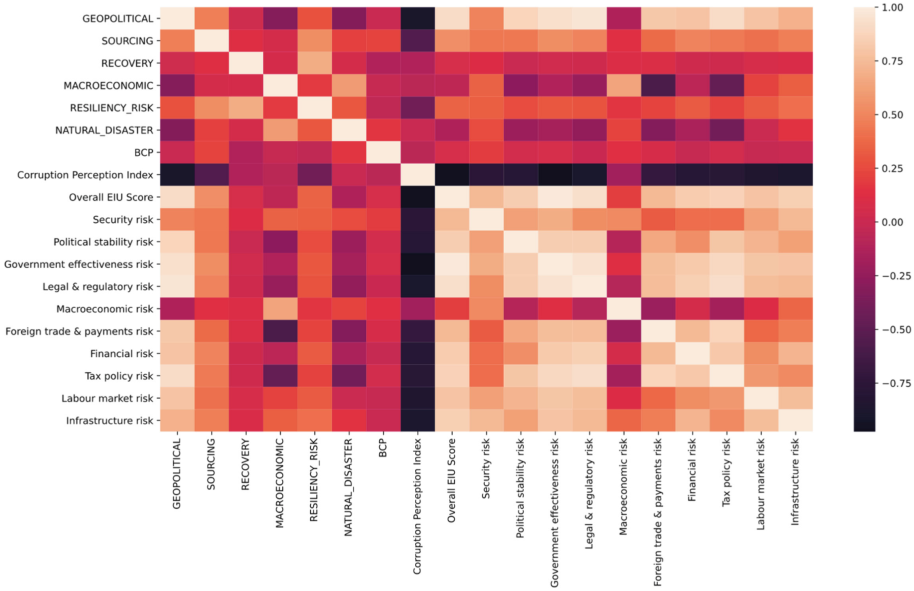
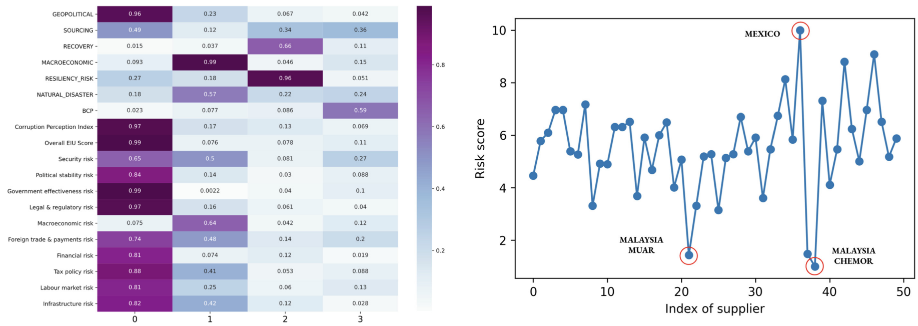


Fig. 3. Correlation matrix of 19 risk criteria for enterprise server product

The results of the factor analysis is shown in Fig. 4a. When conducting a factor analysis, it is frequently necessary to determine how many component variables to keep. Here, we determine the number of factors based on Kaiser Criterion that proposes to extract factors with an eigenvalue greater than 1. The eigenvalue in factor analysis is a measure of how much of the observed variables' common variance is explained by a factor. The larger the eigenvalue is, the more variance the factor can explain than a single variable (risk criterion). Based on this, we select four factors for the supplier risk data. The factor loading of a variable quantifies the extent to which the variable is related to a given factor. It finds most of the risk criteria can be included in factor 1, while the business continuity planning (BCP) risk can be treated as an independent factor.

4.4 Score Calculation

We calculate risk scores for each supplier using the processed risk data from factor analysis. Through extensive brainstorm meetings with experts from different departments in the company (e.g., financial, supply chain, procurement, and so



(a) Results of the factor analysis

(b) Supplier risk score

Fig. 4. Results for factor analysis and supplier risk score calculation

on), all quantitative risk criteria are rated as of low, medium and high importance. The higher the importance of the risk criteria, the greater the weight assigned in the calculation of the risk score. Using product "A0001" as an example, the risk score of 50 suppliers is calculated and displayed in Fig. 4b. We highlight the supplier with the highest risk score in Mexico and the two suppliers with the lowest risk in Malaysia.

5 Risk-Aware Supply Chain Optimization

In our problem, the procurement planner needs to make purchasing plans on computer parts that are subsequently assembled into products for end users such as desktop computers and rack mount servers. Some parts are cheap and required in large quantities while others are expensive specialized components that have high cost but low demand quantity. Internally, parts obtained from suppliers are given a part number (PN) with each PN obtainable from a single supplier. To enable choice among a selection of suppliers, parts may be grouped into APGs, defined by equivalent specifications. For example, consider a range of storage components, different brand hard disks with the same capacity and RPM values may be grouped into an APG. The demand for parts is defined by APG, although parts are purchased by PN from suppliers.

Since contracts with suppliers are typically agreed on a long term basis, our goal is not to recommend suppliers, but uses an established list of contracted suppliers to recommend a default risk-aware part procurement strategy. In addition to the per-part cost of suppliers, two additional factors must be considered. Firstly, suppliers may offer rebates on some of the parts they sell in the form of either a percentage discount or as a per-part discount, if a target quantity of eligible parts is purchased. Since either a percentage discount or a per-part discount can each be expressed in terms of each other, we only implement the percentage discount, and express the per-part discount contracts in terms of percentages. Incentives are not typically agreed for a single part but across all parts ordered from a supplier matching a particular technical specification and importance in the supply chain. Since APGs are an internal concept and apply across suppliers, it cannot be assumed that there will be a convenient correspondence between APG membership and rebate eligibility. Secondly, in order to maintain a good relationship with each supplier, a minimum purchase level per supplier should be achieved, such that a percentage of the demand for each APG is allocated to each supplier that offers parts in that APG.

The notation used in the optimization methods introduced in this section is given in Table 1.

Table 1. Key notations used in optimization solutions.

Indices	
i	Supplier index from set $\mathcal{I}$
j	Part index from set $\mathcal{J}$
k	Alternative Parts Group set index from set $\mathcal{K}$ Each k is a set of parts, $j \subset \mathcal{J}$
l	Incentive index from set $\mathcal{L}$. Each l is uniquely linked to 1 supplier i. Each l is a set of parts, $j \subset \mathcal{J}$
Decision variables	
$y_{i,j}$	Number of part j obtained from i,
$z_{i,j}$	Binary variable indicating if the incentive threshold is crossed for supplier i and for part j
$\zeta_{i,l}$	Variable indicating the number of part j qualifying for rebate
Parameters	
r_i	Risk score of supplier i, normalized to $[0, 1]$
ψ, ψ_j	Risk tolerance level for whole system and for part j individually
$c_{i,j}$	Per-part cost of obtaining j from i
$\theta_{i,j}$	Minimum purchase threshold imposed by supplier i for part j which becomes 0 if disrupted under scenario s
$\lambda_{i,l}$	Incentive threshold for supplier i for scheme l
$\mu_{i,j}$	Rebate percentage if incentive threshold is crossed for i on part j
d_k	Demand for part group k
$\gamma_{i,j}$	Capacity for supplier i, part j

5.1 'Bang for Buck' (B4B) Baseline

The first method to consider is a simple ranking-based approach that does not use scenarios, where suppliers are ordered by their risk score, and, once any minimum order requirements have been satisfied, parts are allocated with priority to the lower risk suppliers, meeting incentive thresholds until all demand has been met. If demand remains after incentives have been satisfied, a default allocation increment should be set, to allocate remaining demand incrementally to each supplier in turn. The best value for the default increment would be a subject for experimentation. The resulting solution will generate two values: the cost of the solution, and the risk score of the solution. The method of calculating overall risk score can be left open for further development, but a reasonable metric would be to express the risk as a percentage or probability in the range $[0, 1]$ of all supplier risk scores, normalised to the $[0, 1]$ range, multiplied by the proportion of all required parts obtained from them, as shown in (2). These two output values will provide a basis for comparison with other methods. The usable output of the method is a default allocation strategy in terms of the numbers of parts that should normally be ordered from suppliers.

$$risk = \sum_i \sum_j r_i \cdot \frac{y_{i,j}}{\sum_j d_j} \tag{2}$$

The algorithm is as follows:

1. Sort the list of suppliers in ascending order of risk score.
2. Allocate parts to buy from each supplier with minimum spend agreement, enough to satisfy the minimum. If there is still unsatisfied part demand, continue.
3. Going through the supplier list in order: if any have rebate incentives, satisfy them. If at any point the total demand is satisfied, end the algorithm. If the end of the list is reached with remaining demand, continue. Given that multiple parts can be part of an incentive scheme, move to the next supplier as soon as the incentive scheme is satisfied.
4. If unsatisfied demand for an APG remains, the leftovers can be distributed among the suppliers with parts in that APG in increments, with priority given to the suppliers with lower risk scores.

5.2 Risk-Constrained Optimization (RCO) Model

Risk-Constrained Optimization (RCO) is a methodology developed in engineering design to optimize performance while remaining within key safety limits [3]. A typical formulation maximizes or minimizes a quantity while ensuring that the probability of failure for a given plan remains below a chosen safety threshold. Thus, rather than considering the cost of failure and trading the cost off with the potential benefits of a plan, failure is a hard constraint to be avoided. We can employ an analogous idea in a the context of this supply chain problem, where, instead of considering the probability of a disruption in the supply chain, we set a limit on the total risk permitted in the system using the risk score in (2).

Our risk-constrained approach needs to account for the features required by our company, namely APGs, rebates, and minimum purchase requirements. The formulate the following set of rules for the optimization to enforce:

– The cost of the allocation is the total cost of buying the required parts from the suppliers at their per-part cost, offset by any rebates that are activated.

– Any minimum spend requirements with suppliers must be met (in this case, this is as a percentage of the demand for each APG that the supplier offers parts for).
– If the number of parts that are part of a rebate scheme with a supplier exceeds the incentive threshold quantity, a percentage rebate is applied to offset the total cost of those parts.
– There are no reductions to capacity or increases in cost due to disruption events, so the total demand for parts must be met. Since parts are members of Alternate Part Groups (APGs), demand satisfaction is counted for the total demand for each part group.
– The risk score for the allocation cannot exceed a set threshold.

$$\min \quad \sum_i \sum_j \Big(y_{i,j} c_{i,j} - \mu_{i,j} c_{i,j} z_{i,j} \Big) \tag{3}$$

$$\sum_{j \in k} y_{i,j} \geq \theta_{i,k} \quad \forall i, k \tag{4}$$

$$\lambda_{i,l} \zeta_{i,l} \leq \sum_{j \in l} y_{i,j} \quad \forall i, l \tag{5}$$

$$z_{i,j} \leq \gamma_{i,j} \zeta_{i,l} \quad \forall i, l, j \in l \tag{6}$$

$$z_{i,j} \leq y_{i,j} \quad \forall i, j \tag{7}$$

$$\sum_i \sum_{j \in k} y_{i,j} \geq d_k \quad \forall k \tag{8}$$

$$\sum_i \sum_j r_i \frac{y_{i,j}}{\sum_j d_j} \leq \psi \tag{9}$$

$$\sum_i r_i \frac{y_{i,j}}{d_j} \leq \psi_j \tag{10}$$

Equation (3) is the objective we want to minimize, combining the per-part cost with any rebate offset. Equation (4) enforces the minimum purchase requirement for the parts in each APG offered by a supplier. (5)–(7) determine if the threshold required to activate a rebate on a particular part has been crossed and therefore the amount of parts that are discounted. (8) ensures that the demand for each APG is satisfied. (9) and (10) ensure that the risk tolerance threshold is not crossed for either the whole problem, or per-part if there are critical individual parts for which the user wishes to specify a particular risk tolerance level.

5.3 Numerical Results

For the purpose of verifying our model, we constructed a number of test cases from anonymized data provided by the company's procurement department. We present results of cases with single APGs, and then for a full dataset over various 3-month periods. Both the B4B and RCO methods were implemented in

Python 3.9, with the optimization solution generated using the CPLEX library, on a desktop computer powered by an Intel Core i7 3.40 GHz with 16 GB RAM.

Comparison Against Baseline. We first evaluate the performance of the B4B baseline method by generating results for a single APG with 3 suppliers, each offering a single compatible part model. The price and risk parameters for each supplier are given in Table 2, with a total demand for the part of 208, and minimum purchase requirement of 10% of demand per supplier. In Fig. 6a we plot the B4B and generate cost values obtained by our risk-aware model with varying risk constraints to serve as a Pareto Front, with the Balance Point indicating the optimal cost obtainable for the risk of the B4B solution. The vertical gap indicates the cost saving achievable at that risk level. As expected, our risk-aware model is able to achieve a considerably better cost performance against the B4B method across all risk levels. Given the superior performance of the RCO, we focus on attempting to outperform the cost totals for historical data in the following results.

Table 2. Parameters used for performance analysis against baseline.

Supplier	Price	Risk
0110	142.558	0.37
0106	155.867	0.15
0107	120.913	0.48

Single APG Results. To verify the correctness of the behaviour of our optimization model, four APGs were considered independently as illustrated in Fig. 5. For each APG, there was a choice of supplier, each offering a different part. The APGs were chosen to highlight two purchasing dynamics - in ‘Scenario 1’, one supplier offered a lower price, while the other offered a lower risk, while in ‘Scenario 2’, the supplier with the lower price also offered lower risk. In Scenario 2, there is a clear preference for one supplier over the other, but when the rebate schemes were introduced, for some APGs, the dynamics changed.

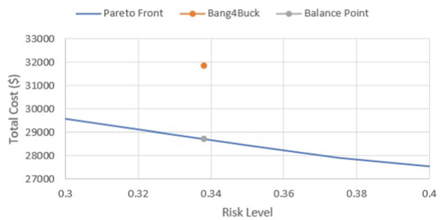
For APG 26, the introduction of a rebate transformed the scenario from a trade-off between price and risk into a straightforward preference for one supplier over the other, with only the minimum required allocation of 10% being given to the other supplier. APG 1 gave the reverse behaviour, with a fixed optimal decision without rebate, but when rebates were made available, the allocation changed as illustrated in Fig. 6b, as the risk constraint changed.

For APG 8, the solution was stable and remained stable with rebates, as expected, while the opposite was the case for APG 35. However, for APG 35, the exact minimum point for the scenario with rebate changed because at looser risk tolerances, rather than choosing the minimum value of the costlier part, our optimization model chooses to buy a slightly higher quantity in order to cross the rebate threshold, resulting in a solution with a lower net cost, than choosing the minimum value and buying the remaining demand from the cheaper part, as shown in Fig. 7.

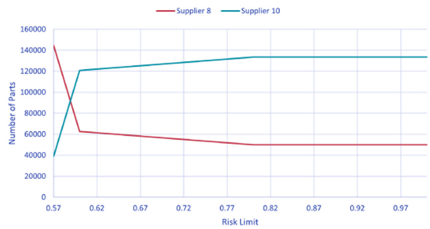
Price vs Risk:
Scenario 1: Lower Price-High Risk vs Higher Price-Lower Risk
Scenario 2: Lower Price-Lower Risk vs Higher Price-Higher Risk

	APG	PNs	Supplier Risk	Price w/o Rebate	Price with Rebate
Scenario 1 → Scenario 2	APG 26	Supplier 11: PN 67	5.52	**120.75**	112.75
		Supplier 8: PN 75	**5.56**	119.57	**113.59**
Scenario 2 → Scenario 1	APG 1	Supplier 8: PN 56	5.56	99.5	**94.53**
		Supplier 10: PN 64	**6.23**	**101.9**	93.75
Scenario 1 → unchanged	APG 35	Supplier 11: PN 44	5.52	**214.06**	**201.06**
		Supplier 8: PN 77	**5.56**	168.16	159.75
Scenario 2 → unchanged	APG 8	Supplier 11: PN 54	5.52	235	215
		Supplier 8: PN 79	**5.56**	**236.42**	**224.60**

Fig. 5. Single APG test cases with purchasing dynamics changing as rebate becomes available.



(a) Pareto Front showing the optimal trade-off between risk and cost for a single part, with the B4B result plotted for comparison.



(b) Cost-Risk trade-off for APG 1 when rebates are available.

Fig. 6. Results to verify correctness of RCO, impact of rebates, and performance against the baseline.

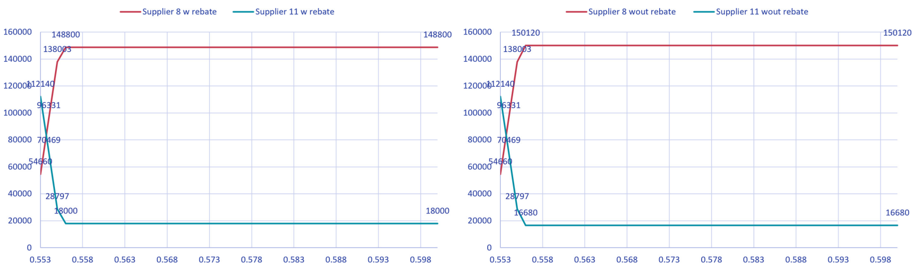


Fig. 7. Cost-risk trade-off for APG 35 with rebate (left) and without rebate (right). For the case with rebate, the lowest value for the costlier part is chosen to be the rebate threshold, as the net cost proves lower than buying the minimum undiscounted part.

These results indicate that when there is a choice of two different parts available to satisfy the demand, the model is able to find solutions that are not immediately obvious to a human observer, but which prove more cost-effective overall. However, since incentive schemes can be satisfied by parts bought from multiple APGs, these examples do not reflect the complexities of actual procurement.

Full Dataset Results. We considered a 3-month period from Jan-Mar 2021, comparing the quantity of parts purchased and the net cost of our optimization model against historical data. We chose a 3-month period, as the threshold number of parts required to trigger a rebate in the provided data was determined by the total quantity purchased in 3 months. Parts with no membership in either an APG nor contributing to a rebate scheme were discarded from both datasets, as they involved no decision-making. The dataset for this 3-month period featured 5 suppliers and 78 PNs after unnecessary parts had been removed. 3 suppliers had incentive schemes, of which 2 were triggered in the historical data. The optimization was able to trigger all 3 while satisfying demand, ultimately purchasing a slightly higher number of parts in order to achieve a lower net cost overall (4.3% cost reduction). Since additional parts could be added to inventory, this should not be a significant concern for the supply chain. Further, as shown in Fig. 8, even a version of the optimization without access to rebates was able to achieve a slightly better cost performance, indicating that more cost-effective part purchases were possible.

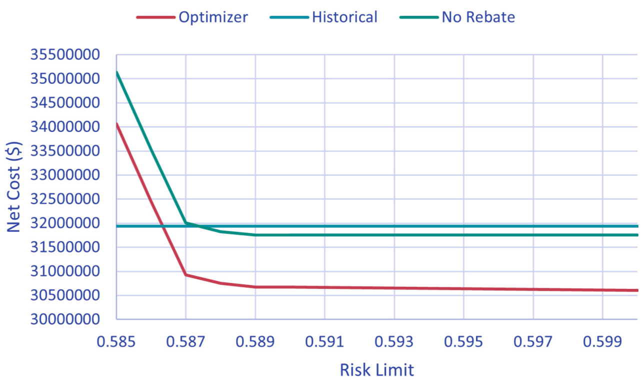


Fig. 8. Net cost values for historical and optimized data as well as optimization without rebates with changing risk tolerance.

By focusing on 3 APGs (APG 7, APG 11, and APG 15) which featured some of the largest savings, some insights are available into why the optimization is able to improve on the historical cost. For APG 7 and 11, the optimizer chooses a smaller selection of parts over the minimum required purchase, with the historical purchases selecting some parts with high cost. For APG 15, the result changes with the availability of rebates. When rebates are available, the optimizer balances the demand between two similarly priced parts, but when rebates are not available, the strictly cheaper part is heavily favoured. This adaptation to the presence of rebates illustrates why the optimization is able to achieve improved cost performance even when rebates are unavailable.

Finally we ran our optimization model on 3 other 3-month periods: April to June, June to August, and August to October. In each case, the goal was to determine whether more rebates could be activated by the optimization. For April to June, the number of parts purchased for Suppliers 8, 10, and 11, the three with rebate schemes, was sufficient to provide a rebate for all, but in the historical purchases, while the allocation to Supplier 8 doubled the rebate threshold, Supplier 10 and Supplier 11 fell short, resulting in only 1 supplier activating their rebates. For June to August, there was a similar case, but Supplier 11 was also activated with only Supplier 10 missing out. For August to October, the total allocated to the three suppliers was inadequate to trigger the rebate for all 3, but an increase from 1 activated supplier to 2 may have been possible. In fact, the optimization was able to achieve rebates on all 3 suppliers in each of the 3 periods, because, due to the consideration of APGs, purchases could be re-allocated from the 2 remaining rebateless suppliers, Supplier 4 and Supplier 7. This resulted in an allocation that was more even between the three suppliers (though still preferring Supplier 8 as in the historical data), but also assigned more parts to the 3 Suppliers and therefore gained discounts for all. The only exception to this was for the case where the risk constraint was set to the tightest limit feasible, in which case Supplier 11 was ignored as far as possible, and therefore could not achieve the rebate threshold while also satisfying the risk constraint.

From these results, we conclude that considering APGs and incentive schemes that encompass multiple parts, it is possible to take a holistic approach to procurement that results in a global cost reduction that may be challenging for planners to identify due to the scale and complexity of the possible solutions.

6 Conclusions and Further Work

Further developments of this project could pursue a number of possible avenues. The first is the research and development of quantifiable risk impact, allowing realistic scenarios to be generated, and thus a stochastic optimization scenario-based approach could be reconsidered. The second approach could be to consider additional 'risk' metrics, such as quality of parts provided. Thus an additional focus on the proportion of defective parts provided by suppliers may enrich the model beyond focusing on supply disruption type risks. Third, some of the assumptions used in the experimental part of the project could be further examined. In particular, it is assumed that for suppliers with multiple risk scores connected to different sites, the scores should be averaged to get the overall supplier risk, but this may be too simplistic to achieve the best cost-risk balance.

Finally, it is also assumed that all parts in an APG are equally viable and there is no inherent preference for one over another that may lead to a decision that is not purely cost-focused. Examining the impact of changing these assumptions will lead to different purchasing decisions. For example, changing the risk calculation to the maximum site risk rather than the average could lead to much greater variation between suppliers and therefore the allocation dynamic and range of possible risk tolerance tuning will change.

The real-world problem of risk-tolerant cost-effective part procurement is a complex one, with many factors being included in decisions that may not all be reflected in the models in this work. However, the results presented for the problems shown indicate that when correctly specified, an optimization model can find a solution that is much more mathematically explainable and scalable than those that can be derived by simple greedy methods or human planners.

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