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OPTIMIZING PART SOURCING STRATEGIES FOR LOW-VOLUME, LONG LIFE CYCLE PRODUCTS USING SECOND SOURCING AND PART HOARDING

Varun J. Prabhakar, Hannah Allison, Peter Sandborn
CALCE Center for Advanced Life Cycle Engineering
Department of Mechanical Engineering
University of Maryland
College Park, MD 20742

Bo Eriksson
Ericsson AB
SE-164-40, Stockholm, Sweden

ABSTRACT

Long life cycle products, commonly found in aviation, medical and critical infrastructure applications, are often fielded and supported for long periods of time (20 years or more). The manufacture and support of long life cycle products rely on the availability of suitable parts, which over long periods of time, leaves the parts susceptible to supply chain disruptions such as suppliers exiting the market, allocation issues, counterfeit part risks, and part obsolescence.

Proactive mitigation strategies exist that can reduce the impact of supply chain disruptions. One solution to mitigating the supply chain risk is the strategic formulation of part sourcing strategies (optimally selecting one or more suppliers from which to purchase parts over the life of the part's use within a product or organization). Strategic sourcing offers a way of avoiding the risk of part unavailability (and its associated penalties), but at the expense of qualification and support costs for multiple suppliers. An alternative disruption mitigation strategy is hoarding. Hoarding involves stocking enough parts in inventory to satisfy the forecasted part demand (for both manufacturing and maintenance requirements) of a fixed future time period. This excess inventory provides a buffer that reduces the effect of supply chain disruptions on the part total cost of ownership (TCO), but increases the total holding cost.

This paper presents a method of performing tradeoff analyses and identifying the optimal combination of second sourcing and hoarding for a specific part and product scenario. A case study was performed to examine the effects of hoarding on both single and second sourced parts. The case study results show that hoarding can contribute to a decrease in the cumulative TCO and a decrease in its variance.

Keywords: Total cost of ownership, hoarding, part sourcing, supply chain, obsolescence, electronic parts, life-cycle cost

NOMENCLATURE

ΔC_{TCO}	Difference in cumulative Total Cost of Ownership of a part
C_{ASYj}	Assembly Cost for a part in year j
C_{FFj}	Field Use Cost for a part in year j
C_{INVj}	Holding (Inventory) Cost without Disruptions for a part in year j
C_{PROCj}	Procurement Cost for a part in year j
C_{SUPj}	Cost to Support a Source for a part in year j
C_{TCO}	Cumulative Total Cost of Ownership of a part
H	Hoarding Quantity
h	Holding Cost (per part per year)
I	Number of Parts in Inventory
I_E	Excess Inventory (positive values of I)
K	Ratio of $\Delta C_{TCO} / C_{SUP}$
m	Forecasted Part Demand (per year)
P_B	Base Penalty Cost (per part per year)
P_{BO}	Backorder Penalty Cost (per year)
r	Discount Rate
S/E	Shortage/Excess on Backorder Quantity
TCO	Part Total Cost of Ownership
T_H	Hoarding Duration
Y_B	Base Year for Money

1 INTRODUCTION

Products can be categorized into long life cycle and short life cycle products. Popular consumer electronics, such as computers, mobile phones, GPS (global positioning systems), etc., have relatively short lives and are replaced with newer products within a few years of their market introduction (usually 5 years or less). Long life cycle products, such as those used in aerospace, military, communications infrastructure, power plants, and medical applications, are manufactured and remain in use for significantly longer (often 20 years or more). Long life cycle products, because of their relatively low volume requirements, often do not control their own supply chains[1] and must draw their parts from the same supply chain as high-volume products. Electronic parts are a good example where all products, regardless of their market, must draw parts from the same supply chain; the outcome is a relatively high frequency of involuntary part obsolescence [1]. As a result, the assessment and management of parts used in long life cycle electronic products differs significantly from their short life cycle counterparts.

Analyses of optimal sourcing strategies for parts (e.g., split award auctions, etc., [2]) are common in the business management and operations research literature, however, the existing analyses are generally part procurement-price centric. For low-volume, long field life systems, the cost of ownership of parts is not driven by their procurement price [3], so split award auctions and similar approaches have little applicability for this type of product. Part "hoarding" – a type of dynamic inventory policy, violates the basic tenants of lean manufacturing culture that seek to reduce the need for holding and managing large inventories of parts. However, lean manufacturing assumes that suppliers that can provide parts for the manufacturing process dependably and without interruption [4], which is often not the case with electronic parts over long time periods. Disruptions in supply can be extremely problematic for low-volume long life systems that depend on electronic parts when lean manufacturing approaches are used.[2]

Due to varying part demand throughout the life cycle of a product or group of products, part hoarding (as presented in this paper) is inherently a dynamic inventory policy. Various dynamic inventory policies and models have been presented in previous works. Karlin [5] introduced a variable inventory model based on a fluctuating demand distribution. Karlin's model incorporates backlogged demand and its associated penalty cost, but the uncertainty of supply chain disruption is not considered. The model is based on defined periods of equal duration, at the beginnings of which ordering decisions are made. Any time lags between order and delivery within the model are assumed to correspond to these pre-determined periods (i.e., a lag lasts a certain number of periods and the parts are delivered at the beginning of a period). Karlin only presents a model for a lag lasting one period. Supplier disruptions are inherently uncertain (when they occur and how long they last are uncertain), and as such a dynamic inventory policy that reflects this fact is necessary. Zipkin [6] developed a simplified version of Karlin's model. Zipkin's model assumes that each period is stationary and uncertainty only comes into play when the periods are combined. Iyer and Schrage [7] focused on the importance of collecting historical demand data to generate inventory control parameters; however they presented only a deterministic model.

Disruption overlap and uncertainties in disruption date and duration are key factors in the model discussed in this paper. In addition, the authors are not aware of any existing work that treats the effect of part hoarding on second sourcing.

The method presented in this paper builds upon the existing total cost of ownership (TCO) model developed by Prabhakar and Sandborn [3]. The model developed in [3] indicated that that the money spent on part and supplier qualification (categorized as "support costs") are the largest contributors to an electronic part's TCO in low-volume, long life cycle products; in high-volume products, these support costs would be distributed over higher volumes. The model in [8] incorporated the effect of sourcing decisions and showed that when procurement and holding costs are small contributions to the part's TCO, the cost of qualifying and supporting a second source outweighs the benefits of extending the part's effective procurement life through second sourcing.

This paper combines a simplified part total cost of ownership model based on the model in [3] with an inventory/backorder model and a cost penalty model to explore the optimum combination of second sourcing and hoarding.

2 PART TOTAL COST OF OWNERSHIP (TCO) WITH SECOND SOURCING

The model developed by Prabhakar and Sandborn [3] determines the part total cost of ownership. The basic model developed in [3][3] for calculating the effective cumulative total cost of ownership through year i for a part[4] is given in Eq. 1,

$$C_{TCO_i} = \sum_{j=1}^{i} (C_{SUP_j} + C_{ASY_j} + C_{PROC_j} + C_{FF_j} + C_{INV_j}) \qquad \text{Eq.1}$$

The model employs an annual (end-of-year) review policy in terms of inventory replenishment decision-making. For a detailed explanation of the terms in Eq. 1, see [3].

[1] In cases were long-life cycle products do have some control over the supply chain, decision making is complex. The TCO of each part has to be carefully considered when selecting part suppliers.

[2] Of course disruptions are also a problem when lean manufacturing approaches are used for high-volume products, but in the case of high-volume products, disruptions are usually relatively short in duration (e.g., hours or days), whereas in the case of low-volume, long field life products, disruptions due to allocation issues and obsolescence may have durations of months (possibly years).

[3] In [3], procurement cost was included in the assembly cost. For the purpose of clarity, procurement and assembly costs were separated in this paper.

[4] In actuality, the costs in Eq. 1 are per part site, where a part site is the location of a part within a product that could be occupied by one or more instances of the part during the support life of the product. For example, if the part fails and is replaced by a spare part, the cost of the spare is included in the cost of the part site.

The decision to second source a part (instead of single sourcing) is based on the tradeoff between the benefit of extending the effective procurement life of the part by second sourcing and the additional cost of qualifying and supporting the second source. In Prabhakar and Sandborn [9] the additional cost to support a second source is modeled using a learning index and the model developed provides a means to determine the "break-even" learning index required to make a second sourcing strategy viable. The approach in [9] addresses long-term (non-recurring) supply chain disruptions and specifically focuses on disruptions due to part obsolescence.

The case study in [9] showed that the benefit of using a second sourcing strategy is dependent on the value of the ratio $K = \Delta C_{TCO}/C_{SUP}$ where ΔC_{TCO} is the difference in total cost of ownership (i.e., the cost avoided by extending the part's procurement life) and C_{SUP} is the cost to support a source. K can be used to calculate the effective learning index associated with sourcing (see [9]). According to [9], the ratio K can be interpreted from two perspectives: 1) as a threshold, K serves as an indicator for the organization's capability to stream-line qualification and support activities for additional suppliers, and 2) as a target, K can be used to estimate the maximum fraction of support cost that can be duplicated for the second source and still make second sourcing viable.

This paper utilizes the ratio, K, to assess the value of proactively qualifying a second source and/or hoarding an inventory of parts to address the issue of recurring supplier-specific part lead time events. The case study presented in Section 4 utilizes a second sourcing condition of $K = 1$, or the complete duplication of support costs, in order to provide a conservative cost estimate.

Prabhakar and Sandborn [9] show that the primary factors contributing to conditions that favor second sourcing is high holding cost (per part per year). As modeled in [9], the accumulation of high inventory/holding costs over time is further exacerbated for parts with short procurement lives.

3 PART TOTAL COST OF OWNERSHIP (TCO) WITH DISRUPTIONS

This section discusses the incorporation of hoarding mitigation strategies and backorder penalties into an existing part TCO model. The modified model concurrently analyzes the effect of both second sourcing (as discussed by Prabhakar and Sandborn [8]) and hoarding on the part TCO so that companies are able to select the most effective management strategy for their specific needs.

The part TCO model, as presented in [3], calculates the part total cost of ownership from the following inputs: part price, part demand (forecasted and actual), support costs, and supplier (sourcing) information. The model in [3] determines the solution to the idealized case: no supplier disruption.

The backorder penalty model presented in this paper is the next step in the process as it takes the final output (the part TCO)

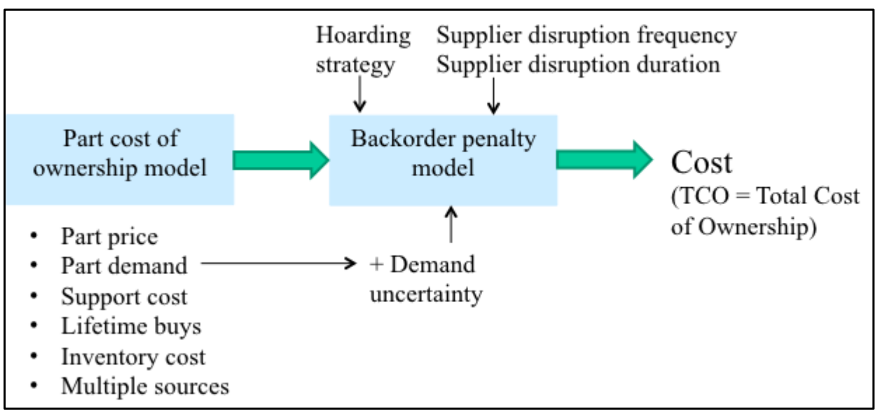

Figure 1: Structure of the total cost of ownership (TCO) model

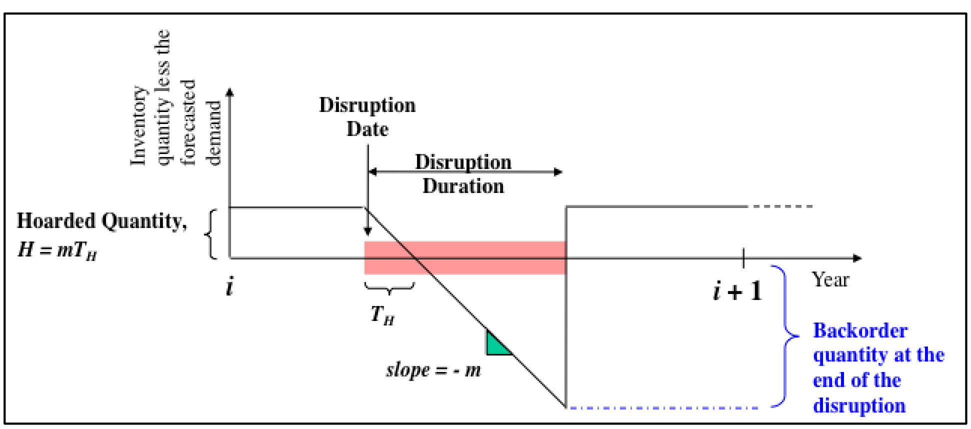

Figure 2: Backorder counting for one year (assuming constant rate of demand, m)

from the original model and incorporates uncertainties (part demand and supplier) and hoarding. Supplier disruptions and part demand uncertainty incur penalty costs (as we will discuss in Section 3.3), which can significantly impact the TCO. The final output of the two steps, as shown in Figure 1, is the sum of the original part TCO without penalty and the penalty costs. This final value is considered the part total cost of ownership (TCO).

3.1 PART HOARDING

When the qualification and support costs associated with multiple suppliers negate the benefits of second sourcing, other mitigation methods can be considered. Additional mitigation methods can supplement the existing sourcing strategy, or replace it. Part hoarding involves stocking a number of parts in the inventory equal to the forecasted part demand of a fixed future time period (e.g., hoard three months' worth of part demand). The forecasted demand may represent the quantity needed for manufacturing and the quantity of spares needed to maintain fielded systems (or satisfy warranty requirements). The excess inventory provides a buffer that lessens the effect of supply chain disruptions on the part total cost of ownership (TCO), but increases the total holding cost. When a supply-chain disruption occurs, the flow of incoming parts ceases and the company begins to draw from their stock of hoarded parts. The presence of hoarded parts in the inventory allows the company to operate as normal for a fixed period of time (determined by the chosen hoarding strategy). If the disruption duration exceeds the predetermined hoarding duration (T_H), then the demand is queued and backordered. The backorder quantity at the end of the disruption, shown in Figure 2, invokes a penalty cost (see Section 3.3).

3.2 CALCULATION OF HOARDING QUANITITY

The method presented in this paper utilizes end-of-year backorder counting. This method assumes that the part total cost of ownership for year i is the cost accumulated between year i and year $i+1$.

As mentioned in the introduction to this section, the hoarding strategy in this paper is defined by the forecasted demand of a fixed future time period. Due to the fact that this demand changes throughout the life cycle of the part, the hoarding quantity is not a pre-determined value. Instead, the hoarding quantity changes from year to year.

If the hoarding duration (T_H, in months) is less than a year, the hoarding quantity for each year (i) within the part's life cycle (with the exception of the final year of support, when no hoarding is necessary) is given by:

$$H_i = m_i\left(\frac{T_H}{12}\right) \qquad \text{Eq.2}$$

If the hoarding duration is greater than a year, then the hoarding quantity for each year (i) is given by:

$$H_i = \sum_{k=1}^{i-1} m_k + m_i\left(\frac{T_H}{12}\right) \qquad \text{Eq.3}$$

Equations 2 and 3 implicitly assume that the forecasted part demand (m, in parts/year), while varying from year to year, is consumed at a constant rate within any given year. The uncertainty associated with of the forecasted part demand impacts the total penalty cost, as discussed in Section 3.3.

When a supplier disruption occurs, new parts are no longer being delivered and the production and support begins to rely on the hoarded inventory. However, if the disruption extends past the hoarding duration, parts are backordered with an additional penalty cost. The number of parts on backorder at the end of the disruption period is considered the backorder quantity.

3.3 CALCULATION OF THE BACKORDER PENALTY COST

One of the major consequences of supplier/production disruption is the accumulation of penalty cost. Whenever demand is not met, a penalty is charged. If disruptions are frequent and/or lengthy or there is a high base penalty cost the cumulative TCO can be dramatically affected. The hoarding strategy can be optimized so as to balance the holding cost associated with excess parts against the possible penalty cost.

In the model presented in this paper, annual backorder penalty (P_{BO_i}) in year i was calculated using:

$$P_{BO_i} = \frac{P_B I_i^*}{(1+r)^{(i-Y_B)}} \qquad \text{Eq.4}$$

where r is the discount rate on money and Y_B is the associated base year for money. Equation 4 incorporates the uncertainty of part demand within the function I_i*, which is defined as the maximum of the following three values: 0, the shortage/excess on backorder quantity (S/E_i), and the parts in inventory (I_i). This function essentially selects the population (due to lead time/disruption or demand uncertainty) affected by the base penalty cost (P_B). The parts in inventory (I_i) are defined within the model as the total number of parts available for production/support at the end of the year, typically as a result of demand uncertainty. A negative quantity indicates a shortage of parts while a positive quantity indicates excess inventory. If there is excess inventory (I_E) at the end of the year, a holding cost (h) is charged per part *instead* of a backorder penalty cost (as excess inventory inherently indicates that no parts are on backorder).

The shortage/excess on backorder quantity is defined as the number of parts that are unavailable for production/support during a lead time event[5] - a negative quantity indicates a shortage of parts. This excess/shortage is essentially the error due to part demand and disruption uncertainty. For the first year of a supplier disruption, this value is calculated by:

$$S/E_i = H_i - m_i D_i \qquad \text{Eq.5}$$

[5] A lead time event is defined as a period of time during which parts are not being delivered (primarily due to supplier disruption)

where D_i is the annual downtime. If the disruption extends past one year, the shortage/excess on backorder quantity is quantified for all subsequent years by:

$$S/E_i = I_i - m_i D_i \qquad \text{Eq.6}$$

The sum of the annual backorder penalty cost and the holding cost on excess parts are added to the part cost of ownership (as calculated in [9] using Eq. 1) to produce the annual part TCO.

3.4 CALCULATION OF PART TOTAL COST OF OWNERSHIP (TCO) WITH DISRUPTIONS

As discussed previously, the part total cost of ownership model presented in this paper expands upon the capabilities of the cost model presented in [9] by incorporating hoarding and backorder penalty cost. The output of the model in [9], the part total cost of ownership without disruptions, effectively serves as the baseline annual cost.

Uncertainty is introduced into the model through the generation of random supplier disruptions. The disruptions are modeled using a three-parameter Weibull distribution (which was selected for generality, but could be replaced with any other distribution) defined by user-supplied parameters. The penalty cost associated with these disruptions is then calculated using Eq. 4. The user-selected hoarding strategy, discussed and calculated in Section 3.2, comes into play within the calculation of the penalty cost.

The final annual part TCO (Eq. 7) is estimated by adding the penalty cost (associated with the supplier disruptions) and the holding cost associated with excess inventory (due to the hoarding policy selected and part demand uncertainty) to the baseline annual part TCO calculated using [9]. The C_{INVj} term from Eq. 1 was replaced with hI_{E_j} in Eq. 7 in order to reflect the inventory counting method detailed in Section 3.3. Note that in years where holding cost (h) is charged, there are no parts on backorder (and vice versa).

$$C_{TCO_i} = \sum_{j=1}^{i} (C_{SUP_j} + C_{ASY_j} + C_{PROC_j} + C_{FF_j} + P_{BO_j} + hI_{E_j}) \qquad \text{Eq.7}$$

To accommodate the uncertainties in the analysis, the model is implemented within a Monte Carlo analysis. The final output of the model, as shown in the case study in Section 4, is a distribution of the likely cumulative TCO per part site over the support life of the product (or family of products) for the mitigation strategies in question.

4 CASE STUDY

The existing model [8], discussed in Section 2, utilizes both forecasted demand and associated part costs (support, procurement/inventory, assembly, and field use) to calculate the part TCO for both single and second sourcing. This section describes a case study performed using the modified part TCO model (Eq. 7) developed in Section 3. All the data used for the example case in this section is provided in the Appendix. The inputs were chosen to mimic the real-world costs associated with an ISDN transformer. However, it should be noted that while the data was carefully selected to produce realistic populations and results, the inputs do not represent true historical data. Each figure shows the results of a Monte Carlo analysis (100 simulated runs) that was employed to include the impact of uncertainty on the part TCO.

The purpose of the hoarding strategy is to delay the negative effects associated with supplier disruption. In other words, part hoarding allows production to continue during a supplier disruption. This extension of the available production period reduces the penalty cost associated with unfulfilled demand. Figure 3 shows the impact of a 20-week hoarding strategy on the available inventory over the 20 year support life of the product considered in this example. The most important trait to notice in Figure 3 is the difference between the number of parts on backorder (which, when non-zero indicate a disruption period) and the number of needed parts in the inventory (negative inventory). In the case shown in Figure 3, the peak amount of negative inventory within each disruption period is less than the peak number of parts on backorder due to the hoarding. Hoarding creates a gap between the start of the disruption and the point when production (or the ability to support the product) stops (due to negative inventory) that allows for shorter overall downtime or possibly no downtime at all.

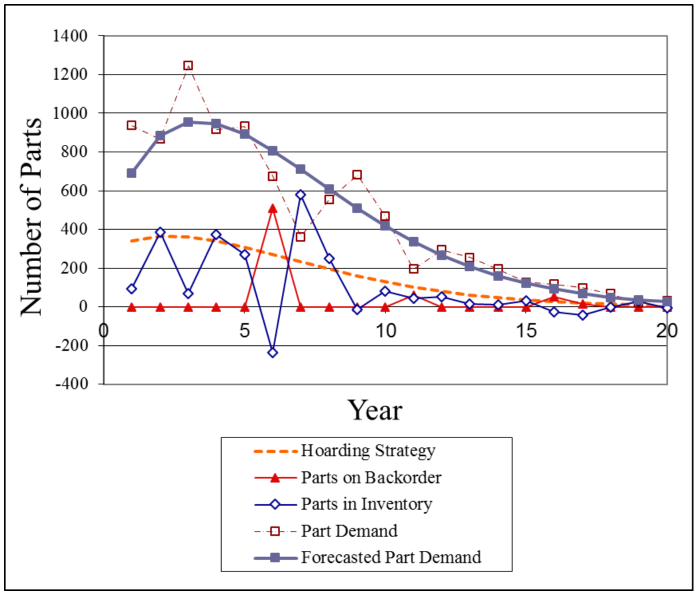

Figure 3: Part quantities over a 20-year period (full part life-cycle). A 20-week hoarding strategy was employed. This figure shows the results for one sample from the population.

The effect of the decreased downtime due to hoarding on the cumulative TCO of the part is shown in Figure 4. Figure 4 shows a comparison of cumulative TCO for a given part assuming no hoarding. A K value of 1 (see Section 2) was assumed in order to demonstrate the worst case of second sourcing, i.e., complete duplication of support costs. Second sourcing decreases the mean cost (from \$47.47 to \$35.55); however a large spread in possible values exists. This spread, i.e., uncertainty, is major source of risk for a company.

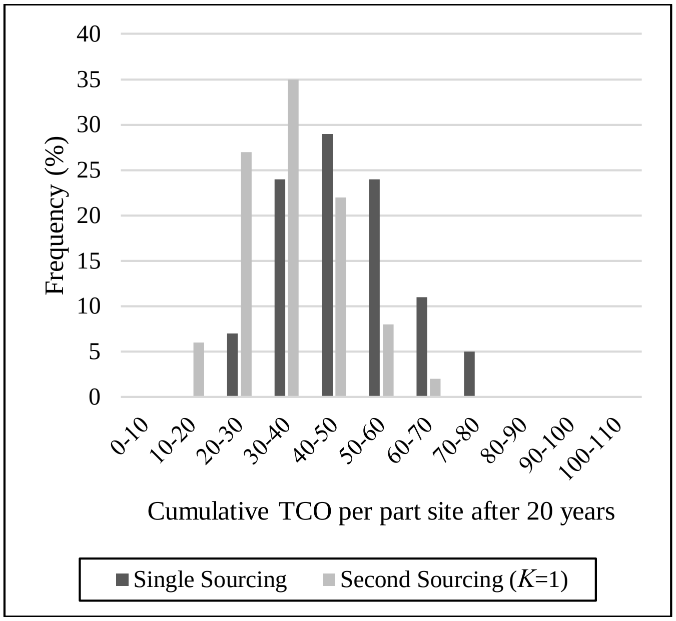

Figure 4: A comparison of the probable cumulative TCO for two sourcing strategies (without any hoarding) for the given inputs.

The effect of hoarding, on both single and second sourcing strategies, is shown in Figure 5. The incorporation of a 20-week hoarding strategy further diminished the mean cumulative TCO when compared to the non-hoarding cases in Figure 3. Also, by reducing the effect of supplier downtime, the spread of the possible TCO was significantly decreased for both sourcing strategies. For the second sourcing case with no hoarding (shown in Figure 4), the standard deviation was \$10.70. When a 20-week hoarding policy was incorporated in Figure 5, the standard deviation was reduced to \$6.67.

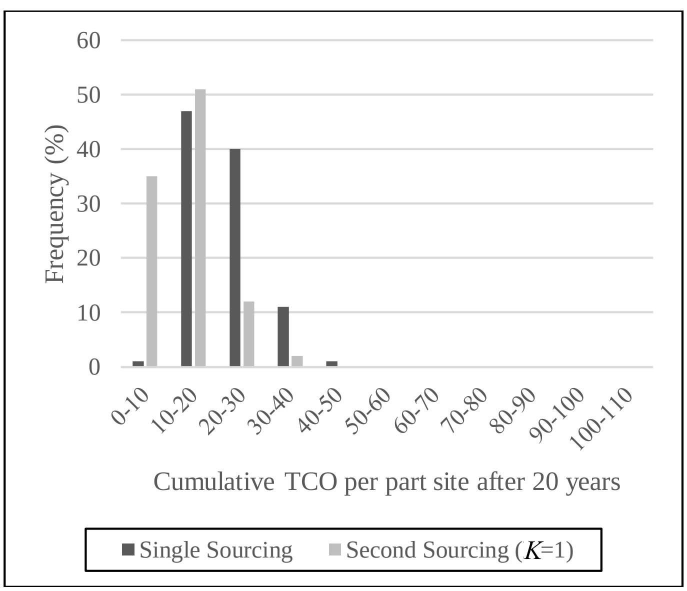

Figure 5: A comparison of the probable cumulative TCO for the two sourcing strategies considered in Figure 3 after the incorporation of a 20-week hoarding strategy.

While the implementation of hoarding as a mitigation strategy was effective under the given set of conditions (see the Appendix for the assumed conditions), hoarding may not always reduce the part TCO. For example, as shown in Figure 6, if the holding cost (per part per year) associated with excess inventory is large then hoarding would only serve to increase part TCO.

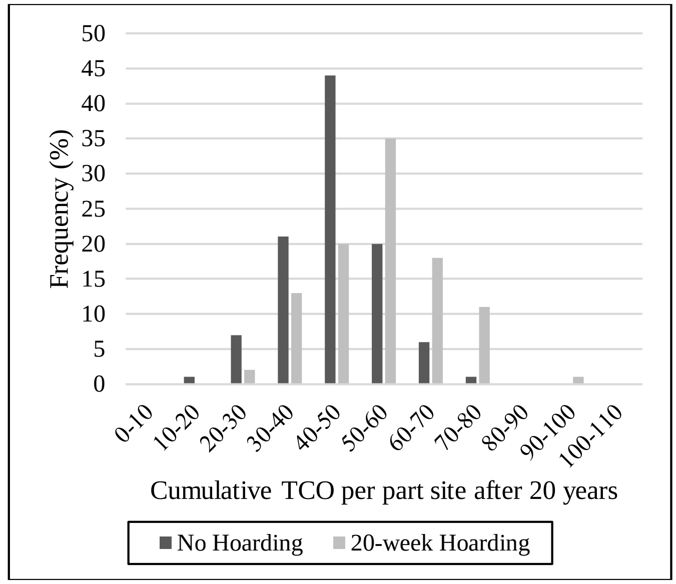

Figure 6: A comparison of the probable cumulative TCO for second sourcing with and without hoarding given a holding cost of \$200 per part per year.

The graph in Figure 6 was generated with the same inputs used in the case study with one notable exception: the holding cost per part per year was increased from \$0.05 to \$200. While this increase in holding cost is unrealistically large, for the given set of conditions in this example, a 20-week hoarding effectively reduced the mean part TCO up to this level of holding cost.

5 DISCUSSION AND CONCLUSIONS

This paper presents a method to compare proactive mitigating strategies, sourcing and hoarding in particular, that provide the means to reduce the effect of disruptions in the supply chain of long life cycle products. As seen in the case study results, the most effective management plan may not be a single mitigating strategy. Instead, a combination of both second sourcing and hoarding has been shown to decrease the mean cumulative TCO.

Hoarding, in and of itself, provides several benefits when it comes to mitigating supplier disruption. In particular, the inventory buffer resulting from hoarding reduces the impact of supplier disruption by decreasing its effective duration. Hoarding is also an effective mitigation strategy when there is a large penalty cost associated with backorders (as mentioned in Section 3.2) as the added holding cost is outweighed by the possible penalties. The conditions under which hoarding is a viable mitigation alternative are application specific and, in the example case discussed in this paper, specific to low-volume, long manufacturing and support life products.

The calculation of backorder penalties associated with part demand uncertainty and supplier disruption is another important aspect of the part total cost of ownership model. Forecasted part demand is typically idealized, and the model presented in this paper accommodates the consequences of any discrepancy between forecasted and actual demand. In addition, the same backorder penalty model can be applied to backorder parts (unmet demand).

In the case study, the incorporation of concurrent proactive mitigation strategies and backorder penalty cost calculations was shown to dramatically affect the part total cost of ownership.

A potentially interesting issue that is highly dependent on sourcing and hoarding is the optimal design reuse of parts within multiple products. When parts are reused, supply chain disruptions can quickly offset savings due to part commonality depending on the availability of finite resources to resolve problems on multiple products concurrently. This issue has been addressed in [10], but it has not been treated in the context of sourcing and hoarding optimization.

6 ACKNOWLEDGEMENTS

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8 APPENDIX - Case Study Inputs

This appendix contains all the inputs used to generate the case study in Section 4. Some of the following inputs populate the models described in [3] and [9], which have not been reproduced in this paper.

Table 1: Inputs for the Part TCO model discussed in Section 2. The highlighted values are also used in the backorder penalty model presented in this paper. The initial part price and price change per year were modeled for an ISDN transformer. The remaining values were used in the original Part TCO model [3].

Ratio, K	1
Effective Procurement Life (years)	20
Discount Rate on Money (r)	10%
Base Year for Money (Y_B)	0
Lifetime Buy Overbuy (fraction of demand)	10%
Holding (Inventory) Cost (per part per year)	$0.05
Initial Part Price (all suppliers)	$0.39
Price Change (per year)	+8.5%
Product Support Life (years)	20

Table 2: Support Cost Inputs. Inputs that were combined and analyzed in the Part TCO model as discussed in Section 2 and detailed in [3].

Product-Specific Approval	$200
Initial Approval	0
Annual Part Data Management	$200
Annual Production Support	$600
Annual Purchasing	$400
Obsolescence Case Resolution	$7,500
PSL Qualification	$10,000

Table 3: Input variables used to generate sample demand populations. The highlighted values were combined using a Weibull function to generate the forecasted part demand values shown in Table 4 (generated before analysis and held constant throughout the Monte Carlo analysis). These parameters were selected in order to produce a population that closely mimics that of an ISDN transformer (with peak demand occurring in year 3 of production). The final variable, demand uncertainty, defines the accuracy associated with the forecasted part demand. A random Gaussian function, which combines this uncertainty and the annual forecasted part demand, is employed to generate actual annual demand values for each Monte Carlo run.

Total Part Volume	9,000
Shape	1.5
Scale (years)	7
Demand Uncertainty[6]	0.25

[6] Demand uncertainty is expressed in terms of standard deviation from the annual quantity.

Table 4: Annual demand inputs (held constant throughout analysis). The number of product designs indicates how many products utilize the part in question each year. If a new product was introduced, a product-specific approval cost, from Table 2, was added to the annual TCO (as discussed in [3]). The forecasted part demand was generated using a Weibull function and the parameters in Table 3.

Year	Product Designs	Forecasted Part Demand (Mean)
1	1	691
2	1	885
3	2	954
4	2	946
5	2	891
6	2	807
7	2	709
8	2	608
9	2	509
10	2	418
11	2	337
12	2	268
13	2	209
14	2	161
15	2	123
16	1	92
17	1	68
18	1	50
19	0	36
20	0	26

Table 5: Additional Inputs. The base penalty cost (B_P) was a direct input for the model discussed in Section 3.2 while the hoarding duration (T_H) was utilized, as shown in Section 3.1, to generate the annual hoarding quantity (H). The number of sample runs indicates the number of simulations that were run to generate Figures. 3-6.

Base Penalty Cost, B_P (per part per year)	$300
Hoarding Durations, T_H (weeks)	0, 20
Sample Runs (Monte Carlo analysis)	100

Table 6: Sourcing Specific Inputs. The following values were utilized to generate (via a three-parameter Weibull function) the supplier disruptions for each Monte Carlo run. [7]

	Supplier X			Supplier Y		
	Location (time)	Shape	Scale (time)	Location (time)	Shape	Scale (time)
Interval (years)	5	1	0.5	5	1	0.5
Length (weeks)	52	1	0.6	52	1	0.6
Part Procurement Life (years)	20	0	0	20	0	0
Analysis Run-in Time (years)	25	0	0	--	--	--

[7] Single sourcing used only Supplier X, second sourcing used both Supplier X and Y.