Proceedings of the 2015 Winter Simulation Conference
L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, eds.

QUANTIFYING VARIABILITY IMPACTS UPON SUPPLY CHAIN PERFORMANCE

Julie A. Castilho
Thomas E. Lang
David K. Peterson
Vitali Volovoi

LMI
7940 Jones Branch
Tysons, VA 22102, USA

ABSTRACT

Efforts to control variability in segments of the supply chain can bring about counterintuitive results. This illustrates the importance of employing analytics in support of any supply chain process improvement or policy initiative. Modeling and simulation (M&S) helps managers identify improvements that will positively affect the supply chain's performance. M&S provides a way to evaluate the relative effects of budgetary decisions on cost, performance, and readiness over a variety of timeframes. M&S also provides a structured methodology to quantify process improvements and variability reductions. Analysis of the Department of Defense supply chain identified three recurring sources of variability: 1) procurement lead time, 2) depot repair time, and 3) retrograde. To evaluate the effect of variability, we employed three hierarchically integrated models: a system dynamics model for strategic decisions; 2) an analytical readiness-based sparing model for tactical decisions; and 3) a discrete event simulation model for logistical and operational performance decisions.

1 INTRODUCTION

The objective of our research was to investigate opportunities for improving supply chain precision and reliability by reducing the level of variability across the five supply chain process areas of Plan, Source, Make/Repair, Deliver, and Return. We identified the scenarios used in this modeling and simulation (M&S) effort through interviews with stakeholders, reviews of previous and ongoing studies, and data analysis related to variability within the Department of Defense (DoD) supply chain. This provided the basis for using M&S to estimate the impact of variance reduction initiatives on cost, performance, and readiness.

DoD supply chain analysts face the challenge of modeling the interrelationships between a host of ever-finer budgetary decisions. It is important to balance resource requirements against operational risk to capture the desired blend of system reliability and availability at an affordable cost. Unfortunately, no single M&S method completely fulfills this need. Thus, in this research, we employed a hierarchically integrated M&S approach (see Figure 1).

This integrated modeling architecture captures the behavior of key supply chain processes (Plan, Source, Make/Maintain, Deliver, and Return). It enables the estimation of supply chain performance across multiple echelons, in a variety of time scales, and from several important modeling perspectives (strategic, tactical, and operational). It also provides a structured environment for quantifying the effects of variance reduction in a repeatable, rigorous manner. This enables more robust solutions: each model can be used to cross-check and calibrate the other models' performance.

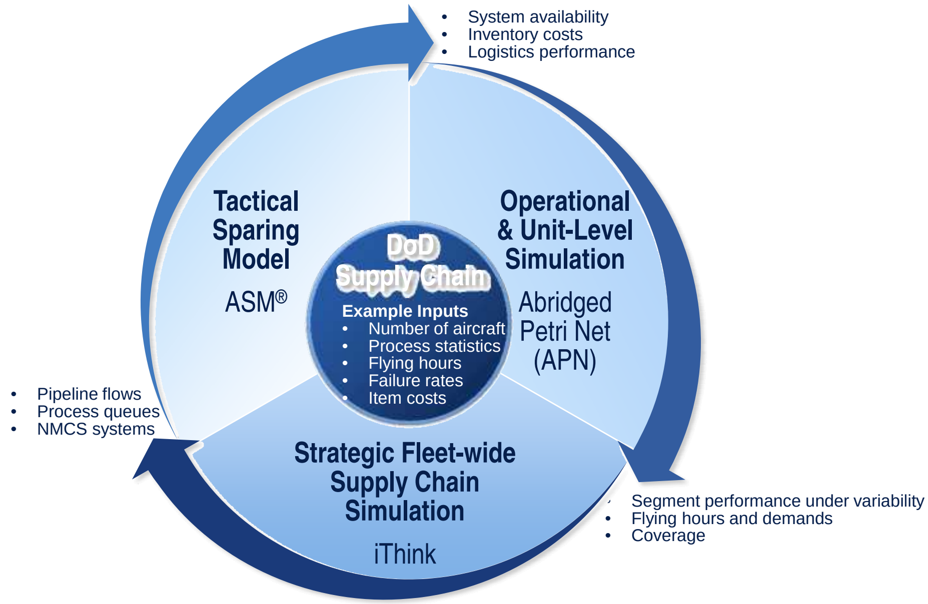

Figure 1: The integrated architecture incorporated three models.

2 BACKGROUND

The integrated architecture for this work incorporated three models, as shown in Figure 1. A system dynamics model, iThink®, was used to assess supply chain variability at the strategic level; an analytical optimization model, the Aircraft Sustainability Model® (ASM®), was used for tactical-level sparing assessments; and a discrete-event simulation model, Abridged Petri Nets (APN), was used for operational and unit-level performance simulation.

2.1 Strategic: System Dynamics with iThink

A system dynamics (SD) model of the Joint Strike Fighter lifecycle cost, developed in iThink, was used to assess variability at the strategic or fleet-wide level (Brunson et al. 2005). SD models are used to understand the behavior of complex systems. They are particularly useful because they predict the behavior of nonlinear phenomena at an aggregate level; when the individual item characteristics are important, discrete-event simulations are used. This is accomplished through the use of "stocks," which are states in a process, and "flows," which are the transitions from one state to another. Quantitative requirements can be placed on the stocks (such as a capacity constraint on a repair facility) as well as on flows (such as the transportation time to the repair facility).

2.2 Tactical: Analytical Optimization with ASM

Traditional inventory models are typically single item models with a uni-directional flow of materials from producer to consumer, where the lead time variance is estimated from a joint distribution of the mean and variance of demand during lead time and the mean and variance of lead time. In these models, smaller demand or lead time variances do lead to a smaller variance estimate of demand during leadtime. However, this type of joint distribution variance estimation does not extend to bi-directional, multi-segment, reverse logistics models. In the latter case, the Vari-METRIC approach to estimating segment variance sequentially and in an iterative/building fashion is the standard methodology (Sherbrooke 2004).

The ASM sparing model was used to evaluate tactical-level supply chain management decisions, such as spares requirements and allocation. The ASM model is an adaptable analytical optimization tool (employing Vari-METRIC logic) that quantifies the effects of variation in terms of inventory cost and performance (i.e., operational availability, or Ao) at a system or an item level. The tactical model uses item-level data (such as demand rates, maintenance times, transportation times, and unit cost) in conjunction with a wide range of operating scenarios (Kline et al. 2013).

Using a marginal analysis approach, the ASM model ranks possible additions to the spares inventory in terms of benefit per dollar. Spares with the greatest benefit per dollar appear at the top of a ranked “shopping list,” thus guaranteeing the spares mix is both effective and efficient. Accumulated costs and the resultant system availability are tracked as the shopping list is developed. The result is a curve that relates overall inventory investment to projected system availability.

2.3 Operational: Discrete Event Simulation with APN

A discrete event simulation model (DES), created in APN, was used to assess logistical and operational performance throughout a representative supply chain (Volovoi 2014).

APN structures are state-space-based so the dynamics of a system can be fully captured (the state of the system is inferred based on the states of its individual components). A system is modeled in terms of its static (state) and dynamic (token) components. The places that tokens (in our model the tokens represent aircraft) occupy define a particular state of the system (operational, awaiting maintenance, etc.), and tokens transition between places, simulating changes in the system state. Transitions between places are described by rules for token movements, and transitions only fire when they are enabled (i.e., if certain conditions are satisfied).

Unlike standard DES tools, APN graphically models failure dependencies and their propagation as moving tokens that visually represent the system dynamics associated with those failures. APN’s parametric flexibility contributes to its modeling robustness; if you can describe the system’s operation, you can build an appropriate network model.

3 SUPPLY CHAIN SEGMENTS

We used M&S to explore the relative effects of variance reduction initiatives and to quantify the potential benefit of such initiatives in terms of cost, performance and readiness. Our analysis focused on three areas: 1) procurement lead time, 2) depot repair time, and 3) retrograde time.

3.1 Procurement Lead Time

Procurement lead time (PCLT) is the length of time required to replenish stock from external vendors at the wholesale level (Pouy et al. 2008). Within the DoD, an item’s procurement lead time is a key factor in determining when an inventory control point (ICP) must place an order to replenish its stock levels and how much stock it must maintain during the period between when a procurement is generated and ordered material is delivered.

PCLT is composed of two subordinate times: administrative lead time (ALT) and production lead time (PLT). ALT begins when the need to purchase material is identified and ends when a contract to deliver the material is awarded to a supplier. PLT begins with the award of a contract and ends with delivery.

Several factors that contribute to PCLT variability were identified, such as: delays finding qualified vendors, inadequate responses to solicitations, evolving federal procurement practices, Diminishing Manufacturing Sources and Material Shortages (DMSMS), inadequate or missing technical documentation, and supply chain disruptions.

3.2 Depot Repair Time

Depot repair time (DRT) starts with the base NRTS (not repairable this station) decision and ends with the completion of item repair at the depot (Perry et al. 1987).

Several factors contribute to DRT variability, including too few repairable carcasses, constrained repair shop capacity, lack of repair parts, mismatches between predicted workload and realized workload, and imperfect repairs.

3.3 Retrograde Time

Retrograde time (RET) is the time that elapses when a failed item is shipped from the base to the depot (Mesaros et al. 2008). Increases in RET can tie up scarce distribution depot resources.

Incomplete, mislabeled, or unlabeled shipments can lead to cargo frustrated at transportation nodes, which contributes to lengthy and variable retrograde times. This leads to repairable carcass starvation at depot repair, congested intake processes at depot supply receiving, and bottlenecks in the carcass breakdown process.

4 METHODOLOGY

This M&S approach provided an environment that spanned strategic, tactical, and operational perspectives, with sufficient flexibility to accommodate a diverse set of supply chain activities and organizational levels. The purpose of this approach was to provide quantitative insights into the likely effects of alternative variability reduction options. All modeling began with the same fundamental baseline settings that are listed in Table 1.

Table 1: Baseline M&S parameter input settings.

Description	Value
Length of simulation	4 years (1,400 days)
Number of aircraft	50 aircraft
Demands per day	0.75 demands (fixed or lognormally distributed)
Variance-to-mean ratio (VMR)	3.3
Order ship time	1 day
Depot repair time (DRT)	60 days
Retrograde time (RET)	4 days
Procurement lead time (PCLT)	402 days
Condemnation percentage	30%
Aircraft availability target	90%
Unit cost per spare	$195,256
Number of bases	Single, composite base
Initial assets at base	144 assets (constant for all scenarios)
Total buy cost	$28,116,864

Note that PCLT is much longer than the DRT and RET; it requires a longer simulation to achieve steady state. Scenario 1 (PCLT) is run to 2,800 days, while Scenarios 2 (DRT) and 3 (RET) each have a run time of 1,400 days.

The item-specific parameters (e.g., demand rate, repair time, condemnation percentage, and unit cost) came from an ASM sparing model demonstration dataset and are representative of the first-level indenture of a reparable aviation component. They are shown as an example of the types of parameters included in the model. We did not assume capacity constraints for any supply chain segment.

Once the baseline parameter and scenario settings were established, we introduced variability at key supply chain segments (PCLT, DRT, and RET) to isolate the effects on the system.

The initial spares level (which was determined by the ASM spares model) was held constant across all of the modeling scenarios, and a pipeline variance-to-mean ratio (VMR) introduced variability effects into the sparing computation. We then used iThink to evaluate the supply chain's system-level behavior.

Within iThink, we assigned the supply chain segment of interest a statistical distribution and associated mean and variance values. In order to ascertain the proper alignment between iThink and APN, a regularly scheduled (fixed) demand was used as a test case (Case 1). This case with zero variability of demand was selected to avoid ambiguity in modeling random effects in iThink versus the DES framework. For this test scenario, we were able to successfully match performance indicators for all individual supply chain segments, thus providing assurance that both models effectively modeled the same process with the same parameters. After aligning APN with the iThink results, we used APN to quantify (in detail) the effect of process mean and variability improvements on supply chain segments.

In the next three sections, we lay out the specific parameters used for those runs. The results from all model runs are presented together.

4.1 Scenario 1: Procurement Lead Time

DoD supply chain metrics have shown that the differences between planned ALT and PLT (i.e., the time the inventory control point uses to initiate buys and forecast lead time demands) and actual ALT and PLT are frequently significant.

We investigated the effect of ALT and PLT variability on weapon system supportability. Using representative ALT and PLT data provided by the Army Materiel Command and Naval Supply Systems Command, we estimated the ALT and PLT parameters (JMP® Software from SAS was used to fit this data to statistical distributions and estimate the associated parameters). Each parameter case is described in Table 2. In Case 1 (the simulation alignment case) we treated demand as fixed (deterministic); in Cases 2–5, we treated demand as probabilistic, with a lognormal distribution.

Table 2: Scenario 1 (PCLT) modeling input parameters.

Case	Description	Segment and distribution	Mean (in days)	Std. deviation (in days)
Case 1	Baseline (fixed demand)	ALT (lognormal)	116	180
		PLT (lognormal)	286	370
Case 2	Baseline (probabilistic demand)	ALT (lognormal)	116	180
		PLT (lognormal)	286	370
Case 3	ALT variance reduction	ALT (lognormal)	116	90
		PLT (lognormal)	286	370
Case 4	PLT variance reduction	ALT (lognormal)	116	180
		PLT (lognormal)	286	185
Case 5	ALT and PLT mean and variance reduction	ALT (lognormal)	76	90
		PLT (lognormal)	189	185

Note: Actual values shown provide an example of the types of parameter values included in the model.

4.2 Scenario 2: Depot Repair Time

The DRT value can be further separated into segments: retrograde, breakdown, front shop repair, and assembly. While ASM considers the entirety of the depot repair time process, modeling with APN and iThink focuses on the front shop repair segment.

Depot repair time can be highly variable for a number of reasons, such as problems with too few repairable carcasses, constrained repair shop capacity, lack of repair parts, mismatches between predicted (or scheduled) workload and realized workload, and imperfect repairs (i.e., rework). We explored the effect of reducing DRT variability on weapon system supportability. We used data from Perry et al. (1987) to establish the representative DRT parameters and distributions (see Table 3).

Table 3: Scenario 2 (DRT) modeling input parameters.

Case	Description	DRT distribution	Mean (in days)	Std. deviation (in days)
Case 1	Baseline (fixed demand)	Weibull	53	23.71
Case 2	Baseline (probabilistic demand)	Weibull	53	23.71
Case 3	DRT variance reduction	Lognormal	53	11.86
Case 4	DRT mean and variance reduction	Lognormal	33	11.86

Note: Actual values shown provide an example of the types of parameter values included in the model.

As in Scenario 1, Case 1 was used to align the simulations and employed fixed demand; Cases 2–4 employed probabilistic (lognormal) demand.

4.3 Scenario 3: Retrograde

RET is the amount of time that elapses when a failed item is shipped from the base to the depot. Increases in retrograde time can tie up distribution depot resources and result in delays. These delays, and their associated variability, can lead to repairable carcass “starvation” at depot repair, congested intake processes at depot supply receiving, and bottlenecks in the carcass breakdown process.

We examined the effect of reducing RET variability on weapon system supportability. Representative parameters (see Table 4) were taken from values published by Mesaros et al. (2008) which included descriptive statistics for approximately 70,000 Air Force retrograde transactions. As in Scenarios 1 and 2, Case 1 was used to align the simulations and employed fixed demand, while Cases 2–4 employed probabilistic (lognormal) demand. The actual values are shown here to provide an example of the types of parameter values included in the model.

Table 4: Scenario 3 (RET) modeling input parameters.

Case	Description	RET distribution	Mean (in days)	Std. deviation (in days)
Case 1	Baseline (fixed demand)	Lognormal	4	4.3
Case 2	Baseline (probabilistic demand)	Lognormal	4	4.3
Case 3	RET variance reduction	Lognormal	4	2
Case 4	RET mean and variance reduction	Lognormal	2	2

Note: Actual values shown provide an example of the types of parameter values included in the model.

For his supply chain simulation, Goodrich (2010) used the lognormal distribution to represent the transportation time for palletized shipments in an air cargo system (which we emulated). Case 3, retrograde time variance reduction could simulate RFID improvements, greater emphasis on labeling and marking, etc., while Case 4 could simulate improvements to shipping time (e.g., FedEx airborne vs. truck or ship).

5 DISCUSSION

Given the scenario-based case structure and parameterizations described above, we can illustrate the likely effect of variability in terms of system availability, total assets in the resupply pipeline, and total assets in the specific pipeline segment of interest.

5.1 Effect of Variability on System Availability

System availability is represented by the number of aircraft that are operational. Figure 2 illustrates the effect of a reduction in variability on the average number of operational aircraft once the system has reached a steady state.

As expected, the intermediate cases do not exhibit improvement in system availability. In fact, at steady state (around day 2,800), there was no difference between the baseline and the intermediate PCLT cases. (Note that, in Figures 2, 3, and 4, PLT average values are taken from a 2,800-day simulation run). In all three scenarios, system availability is only affected by concurrent reductions to the process mean and variance.

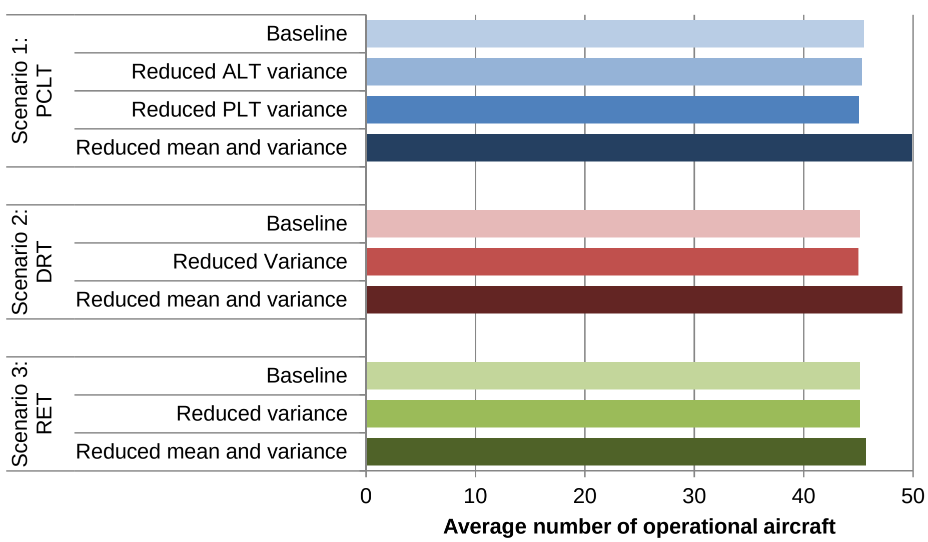

Figure 2: The effect of variability on system availability (under probabilistic demand).

5.2 Effect of Variability on Total Pipeline

Total pipeline represents the number of assets that exist in any segment of the supply chain. Figure 3 illustrates the effect of a reduction in variability on the average number of total pipeline assets in the system, once the system has reached steady state. A reduction in the requirement for pipeline assets means that managers can achieve the same level of equipment readiness with less inventory investment.

Note that, for each scenario, the lowest number of total pipeline assets occurs in the final case (when both the process mean and variance are reduced). In the intermediate cases, reduction of process variance alone has virtually no effect on the number of assets in the total pipeline.

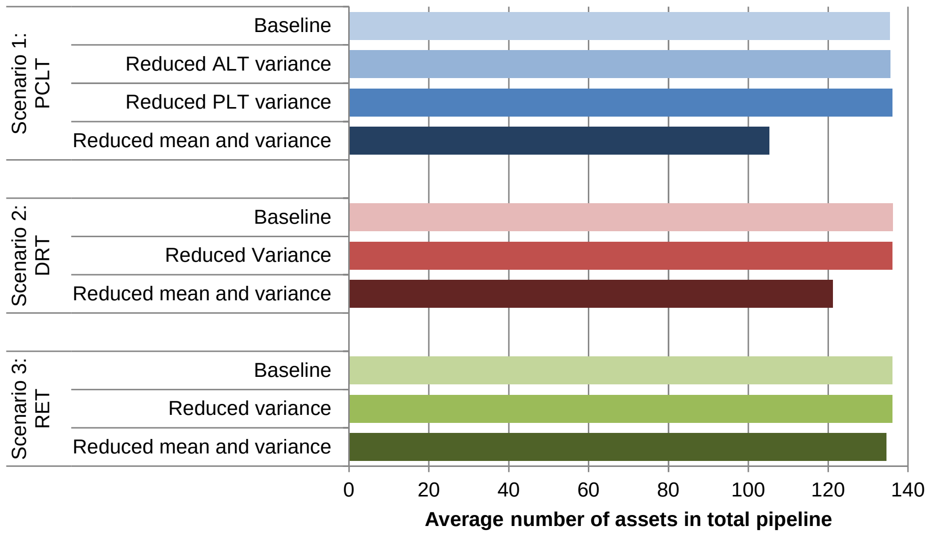

Figure 3: The effect of variability on total pipeline assets (under probabilistic demand).

5.3 Effect of Variability on Pipeline Segments

An examination of the effect of a reduction in variability on the specific pipelines (see Figure 4), corroborated the feedback we received during subject matter expert interviews. It also puts segment-specific observations into a total system context. For Scenario 1, we examined the procurement pipeline. For Scenario 2, we considered the entire depot repair pipeline. For Scenario 3, we observed just the retrograde portion of the depot repair pipeline.

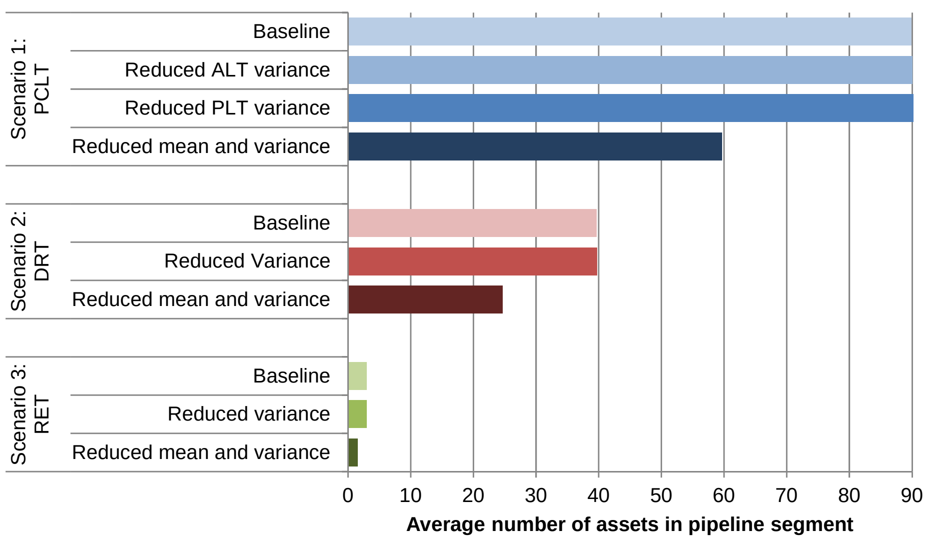

Figure 4: The effect of variability on pipeline segment assets (under probabilistic demand).

Again, the greatest improvement in pipeline segment performance occurs when both the process mean and variance are reduced. (Note that the magnitude of change in each scenario reflects the number of assets flowing through the three pipeline segments of very different durations, which is consistent with

Little's Law from queuing theory.) In the intermediate cases, reduction of process variance has virtually no effect on the number of assets in the specific pipeline segment.

One additional result should be noted about our analysis of variability on pipeline segments. The reduction in assets is most prominent in segments with large process times. In fact, the results are in direct proportion to the relative magnitude of the process being examined. Thus, reducing the mean of the ALT or PLT will have a greater potential effect than reducing the RET mean. Reducing the mean of DRT is somewhere in between. This observation reinforces a central tenet in the practical employment of statistical process control: first bring the process' variance under control, then work to shift the process' mean to an acceptable performance level.

5.4 Comparing the Segment versus Systemwide Perspectives

Classical repair process models (Sherbrooke 2004) recognize the importance of repair pipeline variability. A means for capturing this effect includes the use of binomial and negative binomial distributions to match the variance-to-mean ratio (VMR) of the pipeline that is less than and more than unity, respectively. Sherbrooke (2004) shows a two-indenture example leading to a pipeline VMR > 1 in the presence of spares even when the demands for the lower indenture parts are Poisson processes. For a single indenture scenario, Palm's theorem effectively stipulates that, given a Poisson demand, only the mean of the repair distribution is relevant—regardless of a specific shape of the distribution.

When demand deviates from a Poisson process, the impact of individual segments on the entire supply chain VMR seems to be poorly understood. In fact, it is commonly assumed that variance is effectively additive across the segments, as one would expect if the corresponding random variables are independent. However, as discussed next, this is not always the case. In general queuing theory, the flow of items through a server can be adequately characterized by the first two moments of the inter-arrival and service time distributions along with the number of servers (Whitt 1993). This approximation was used by Fu and Dias (1997) to investigate a repair process with capacity constraints. In this research, since the presence of capacity constraints can complicate the process dynamics, no capacity constraints were considered for clarity in isolating the variability effects. Our approach (and the corresponding APN models), however, can readily incorporate capacity constraints and therefore may be used to study the combined effects of variance interactions and capacity constraints in future research efforts.

Consider a simple scenario—a 20 asset fleet with 20 spare parts. On average, 10 failures occur per unit of time (e.g., month), and the supply chain consists of two sequential repair segments, each averaging one unit of time (therefore, the expected supply chain quantity is 20 parts). No capacity constraints are considered, as consistent with the usual assumptions made in readiness-based sparing. We sequentially modify the distributions of demand and of repair segment 1, without changing their respective means, and observe how the steady-state performance characteristics of the supply chain are impacted. In all of the scenarios, repair segment 2 has a fixed duration (varying the corresponding distribution does not further the qualitative insights).

We simulate the supply chain using APN. In each run, one million samples of Monte Carlo simulation were used with the results (repair pipeline VMR and operational assets) obtained by time averaging over the remainder of the simulation after the warm-up period. (The warm-up period was set conservatively, and for most cases 20-50 time units of simulation were sufficient; however, for Runs 2 and 5 a longer warm-up period of 100 units was used to compensate for a slower convergence due to the service time variability). Variance-to-mean ratios were observed for individual segments and for the entire pipeline, along with the mean number of operating assets and their corresponding VMR. Table 5 summarizes the simulation results.

Table 5: Sensitivity of the pipeline to demand and service segment variability.

	Demand		Repair Seg. 1		Repair Pipeline VMR			Operational Assets		
Run	**Type**	**SCV**	**Type**	**SCV**	**Seg. 1**	**Seg. 2**	**Total**	**Availability**	**Mean**	**VMR**
1	Exponential	1	Fixed	0	1.00	1.00	1.00	91.1%	18.22	0.41
2	Exponential	1	Lognormal	3	1.00	1.00	1.00	91.1%	18.22	0.41
3	Lognormal	1	Fixed	0	0.94	0.94	0.97	91.3%	18.27	0.35
4	Lognormal	1	Exponential	1	0.97	0.99	0.98	91.2%	18.25	0.37
5	Lognormal	3	Fixed	0	2.23	2.23	2.48	86.1%	17.21	0.91
6	Lognormal	3	Exponential	1	1.68	1.59	2.17	87.0%	17.40	0.81
7	Lognormal	3	Lognormal	3	1.53	1.65	2.09	87.3%	17.46	0.78

Comparing Runs 1 and 2 confirms Palm's theorem—when the demand follows a Poisson distribution (and the time between the sequential demands follows an exponential distribution), the service time distribution type does not affect the overall supply chain flow. The total pipeline VMR can be inferred from the segments' VMR. Run 3 corresponds to the scenario when the Poisson demand is replaced by a renewal process, with the times between the consecutive demands following a lognormal distribution that matches the first two moments of the exponential distribution. This implies the squared coefficient of variation (SCV, or variance divided by the square of the mean) is 1.

While the impact is still minor, the effect is real, and the VMR of both segments is reduced (to 0.94, although there is a positive correlation between the two values, so that the total pipeline VMR is 0.97). As a result, the system availability is increased (slightly) and the operational VMR is reduced (slightly) as compared to the Poisson distribution. When service follows an exponential distribution (Run 4), the effect is reduced. This is consistent with the common practice of relying on the first two moments for adequate information about the distribution of a process (Whitt 1993).

Finally, let us consider demand where the time between the consecutive demands has larger variance (SCV = 3). As expected, for Runs 5–7, the performance is significantly worse because of the increased variability. Counterintuitively, increasing variance (i.e., the repair segment in Runs 6 and 7) can actually be beneficial, as the total pipeline variance decreases.

In summary, care must be taken when drawing inferences about the effect of individual pipeline segment variability upon overall supply chain performance. In the case of unconstrained (or non-binding) repair capacity under highly variable demand, reducing the repair variance can actually make the overall supply chain performance worse! Taking a more holistic view of supply chain variability is essential.

6 CONCLUSIONS

Modeling and simulation has a critical role to play in evaluating supply chain improvement alternatives. Our research found that well-intentioned efforts focusing on controlling variability in a given segment of the supply chain may bring about counterintuitive results. Further, even for very straightforward process improvements, our results showed that a reduction in the process mean time can be more important than a reduction in variance.

To consider the entire system's behavior when weighing the benefits of variability reduction efforts, it is essential to leverage analytics in support of any supply chain process improvement or policy initiative. For example, statistical process control (SPC) practice recommends distinguishing between variability that occurs as an innate part of the process ("common cause") and is probabilistically predictable, and variability that is not inherent to the system ("special cause") and is not predictable. As Wheeler (2000) notes:

> When your process is predictable you may use the past as a guide to the future. While you may not be able to predict specific future values, you can describe the range of

> routine values to be expected in the future…In addition, a predictable process is one that is operating up to its potential—it will be operating with maximum consistency and minimum variation…On the other hand, an unpredictable process will not be operating up to its full potential: it will not be operating with maximum consistency, it will not be operating with minimum variation, and it will be subject to unpredictable changes.

According to Wheeler (2000), "when a process displays unpredictable behavior, you can most easily improve the process [reliability] and process outcomes [performance] by identifying the assignable causes of unpredictable variation and removing their effects from your process." In the context of our modeling examples, we illustrate the soundness of Wheeler's recommendation when we reduce both the process mean and variance.

Another important insight is that reducing variability in individual segments (even if their duration is significant, such as PCLT) will not necessarily reduce the supply chain's overall VMR when segment capacity is not binding. Thus, reducing the segment's variance may have little or no effect on the supply chain's overall performance (or potentially even degrade the performance). Clearly, the impact of variability reduction under pipeline segment capacity constraints warrants additional future research.

7 RECOMMENDATIONS

In today's highly constrained DoD budgetary environment, it is critical to use M&S to support supply chain policy and practice decisions. Modern M&S capabilities provide the requisite foundation for DoD supply chain management policies to be analytically driven, with major decisions fully supported by quantitative analysis.

As our M&S results revealed, managing and containing supply chain variance is only part of the picture. Reducing the process mean is also essential. As Hammer (2007) explains: "redesigning processes is often the only way to improve their performance dramatically. Doing so eliminates many of the non-value-adding activities that are the source of costs, errors, and delays and helps companies come up with process innovations…"

Business analytics are especially beneficial for DoD policy development and resource management (Parlier 2014). The complementary power of operations research, advanced analytics, and management innovation offer especially valuable insights with respect to process management and variance reduction. Accordingly, defense managers should consider taking full advantage of the many supply chain analytical tools currently available and integrating these tools into tailored suites of analytical capabilities.

REFERENCES

Brunson, T. A., et al. 2005. "Joint Strike Fighter Spares Study." Report LG301T12. McLean, VA: LMI.

Díaz, A. and M.C. Fu. 1997. "Models for Multi-Echelon Repairable Item Inventory Systems with Limited Repair Capacity", *European Journal of Operational Research* 97: 480–492.

Goodrich, P. L. 2010. "Delivery Time Variance Reduction in the Military Supply Chain." Master's thesis, Air Force Institute of Technology, Wright-Patterson AFB, Ohio. (ADA517388).

Hammer, M. 2007. "The Process Audit." *Harvard Business Review* 85: 111–124.

Kline, R. C. et al. 2013. "User's Manual for the Aircraft Sustainability Models (ASM, ISAAC, SSM): Version 9.25 and Above." Report ASM-UMT1. McLean, VA: LMI.

Mesaros, W. et al., 2008. "Retrograde Transit Normalization Study: A Preliminary Investigation into Variance in Retrograde Processing." *Air Force Journal of Logistics* XXXII: 102–110.

Parlier, G. 2014. "The State of Military O.R." *OR/MS Today* 41: 18–24.

Perry, J. H. et al. 1987. *Improving Depot Repair Cycle Management: A Challenge for Supply and Maintenance*. Report AL614R1. McLean, VA: LMI.

Pouy, M. R. et al. 2008. "Procurement Lead Times for Secondary Items in Defense Inventory Management." Report OSD86T2. McLean, VA: LMI.

Sherbrooke, C. C. 2004. *Optimal Inventory Modeling of Systems. Multi-Echelon Techniques*, Norwell, MA: Kluwer Academic Publishers.

Volovoi, V. 2014. "Abridged Petri Nets," arXiv, http://arxiv.org/abs/1312.2865.

Wheeler, D. J. 2000. *Understanding Variation: The Key to Managing Chaos.* Knoxville, TN: SPC Press.

Whitt, W. 1993. "Approximations for the GI/G/m Queue" *Production and Operation Management* 2: 114–161.

AUTHOR BIOGRAPHIES

JULIE A. CASTILHO is a consultant in LMI's Supply Chain Management Group. She has 7 years of experience analyzing spare parts decisions using a variety of models, including LMI's Aircraft Sustainability Model (ASM®), the Selected Essential Item Stockage for Availability Methodology (SESAME), iThink®, and NASA's Operating and Support Cost Analysis Tool (OSCAT). She has assisted in developing databases and software to support asset tracking and the generation of DoD stratification reports and also has experience programming a range of supply chain applications. She is the 2011 recipient of the SOLE Field Award in Readiness-Based Sparing. She has a BS in mathematics from Otterbein College and an MS in management science from the University of Dayton. Her email address is jcastilho@lmi.org.

THOMAS E. LANG is a senior consultant in LMI's Supply Chain Management Group. He came to LMI from the RAND Corporation, where he was an assistant policy analyst supporting Project Air Force (a federally funded R&D center), where he worked on a variety of research projects, including the design of reliable supply networks for DoD, optimization of overseas basing options for the Air Force, evaluation of advanced materials used by the military, review of incentives for pharmaceutical companies to produce vaccines, and analysis of Russian economic reform. Before joining RAND, he served as a noncommissioned officer in the U.S. Army. He has a BBA and an MA in economics, both from Kent State University, and a PhD in policy analysis from the Pardee RAND Graduate School. His email address is tlang@lmi.org.

DAVID K. PETERSON is a senior consultant at LMI, specializing in readiness-based sparing. He has advised federal agencies on supply chain and operational analytics projects, including reparable inventory management, identifying critical DoD and defense industrial base logistics infrastructure, strategic materiel sourcing, end-to-end logistics management, and aviation operating and support cost data. A former career U.S. Air Force officer, his military service included base- and depot-level supply and maintenance management, graduate-level logistics education, and policy analysis and project management at the senior staff level. He has a BS in biology from Iowa State University, an MS in logistics management from the Air Force Institute of Technology, and a PhD in business administration from the University of North Carolina at Chapel Hill. His email address is dapeterson@lmi.org.

VITALI VOLOVOI is an independent consultant working for LMI. Dr. Vitali Volovoi, formerly an assistant professor in the School of Aerospace Engineering at the Georgia Institute of Technology, has more than 90 journal and conference publications. He received a university diploma with honors in Applied Mechanics from Moscow State University in 1988, and he earned his Ph.D. in Aerospace Engineering from the Georgia Institute of Technology in 1997. His principal fields of expertise are system safety and reliability, risk assessment, analysis and probabilistic design of advanced structures, and structural reliability and optimization. In 2014 Dr. Volovoi was given a NASA Engineering and Safety Center technical excellence award for his contributions to the reliability investigation of the Hubble telescope gyros. His email address is vvolovoi@lmi.org.