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Mitigating disruptions in a multi-echelon supply chain using adaptive ordering ☆

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ABSTRACT

Supply chains often experience significant economic losses from disruptions such as facility breakdowns, transportation mishaps, natural calamities, and intentional attacks. To help respond and recover from a disruption, we investigate adjustments in order activity across four echelons including assembly. Simulation experiments reveal that the impact of a disruption depends on its location, with costlier and longer lasting impacts occurring from disruptions at echelons close to ultimate consumption. Cost functions based on system inventory and service can be quite ill-behaved in these complex problem settings. Expediting, an adaptive ordering approach often used to mitigate disruptions, can trigger unintended bullwhip effects, and hurt rather than help overall performance. As an alternative to expediting interventions, dynamic order-up-to policies show promise as an adaptive mitigation tool. We also find benefits in the dynamic policies from incorporating a metaheuristic parameter search over multiple echelons, yielding significantly better solution quality than embedded unimodal search.

1. Introduction

Disruptions introduce shocks into supply chain systems. Disruptions are often unfamiliar in nature, and not easily resolved. We consider mitigation of the disruptions through adaptive ordering policies in multi-echelon systems that serve as fundamental links in the procurement, manufacturing, and distribution of products among firms within supply chains. The objective is to quickly restore appropriate service and inventory levels, thus reducing the short and long run cost of disruptions.

The causes of disruptions may range from natural (e.g., Japan earthquake and tsunami of 2011) to accidental (Gulf of Mexico BP oil spill of 2010) to intentional (Paris terrorist attacks of 2015, World Trade Center attacks in 2001). With the increase in global business activity, the impact of disruptions could be substantial. Estimated at over $350 billion, the year 2011 was the costliest year ever for natural disasters [1]. Average insured losses from natural causes within the U.S. for the years 2000 to 2013 were $29 billion annually [2]. While each individual disruption has a low probability of occurrence, there is a reasonable chance overall that something big and unexpected will happen. The consequences can be substantial and long lasting, with rippling effects felt throughout multiple business sectors. An Accenture study [3], which polled 151 supply chain executives in large U.S. companies, found that 73% of the firms experienced costly disruptions in the past five years. Of those, it took 36% more than one month to recover and another 32% between a week and a month. Hendricks and Singhal [4] found that following a disruption, firms on average experience a 107% decrease in operating income, 7% lower sales growth, and 11% higher costs. The firms also suffered 33–40% lower stock returns over a three-year period, and share-price volatility rose by 13.5% in the year after the disruption. They offered additional evidence on financial deterioration [5], and market impact [6]. Kumar, Liu, and Scutella [7] extend investigation of the stock consequences of disruptions to markets in India. Filbeck, Kumar, and Zhao [8] show that competitors of disrupted companies also face stock declines. Mitroff and Alpaslan [9] analyzed crisis readiness of Fortune 500 companies over the past two decades. They found that 95% of these companies are not prepared for an unfamiliar disruptive event. Many others have reported

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costly consequences of disruptions as well. See Craighead, Blackhurst, Rungtusanatham, and Handfield [10].

Our study of disruptions in complex multi-echelon inventory systems leads to useful insights about post-disruption mitigation strategies using adaptive ordering policies. The paper is organized as follows. We begin by reviewing prior literature and our field work on electronics case applications. Then we present a set of simulation experiments using a representative four-echelon assembly structure to explore each of the following key research issues.

1) What happens to supply chain system performance in the presence of a disruption?
2) How does expediting affect system performance?
3) How well-behaved is system performance when dynamic order-up-to policies are used?
4) When should analytics or heuristics be applied in system ordering?
5) How do global and line search heuristics compare in solution effectiveness and efficiency?

Our simulation results confirm that disruptions may have long lasting, rippling, and costly consequences on inventory and service within a supply chain, and that expediting efforts introduce cost and may hinder rather than help system recovery. This raises important issues about the widespread use of expediting as the mitigation tool of choice, and inspires our research into ordering approaches capable of mitigating without expediting. Even in the absence of expediting, system cost can be quite ill-behaved. Conventional ordering approaches, which assume unimodal behavior within analytically tractable problems, may be inappropriate for real-world supply chains. This need for managerial relevance suggests fresh methodology capable of relaxing traditional assumptions of unimodality, aggregation, substitutability, independent steady-state distributions, and well-behaved supply and demand functions across multiple stages.

2. Literature review

The related literature falls into four subject categories: disruptions and their treatment, expediting as a mitigation approach, model complications from bullwhip effects, and inventory policies. Within each subject, we organize the literature by research methodology.

2.1. Disruptions

There is a rich body of analytical and empirical work on disruption management. Craighead et al. [10] and Heckmann, Comes, and Nickel [11] provide thoughtful literature reviews. Most analytical work on disruptions relies on uncapacitated single-echelon models, with exponential or geometric failure times, and inventory buffering as mitigation [12]. Specific examples include Berk and Arreola-Risa [13] for an EOQ policy, Parlor and Perry [14] for a (q,r) policy, and Arreola-Risa and DeCroix [15] for an (s,S) policy. See Snyder et al. [16] for a comprehensive review of supply chain disruption models.

Other analytical literature assumes stochastically recurrent disruptions, an order-up-to policy in a single echelon that maintains inventory, and in most cases, shortages backordered, not lost. These papers address applications such as: lead time disruptions from border closures [17], threat level information and evolving risk [18], supplier selection and reliability [19], product mix and supply diversification [20], facility location/allocation [21], and inventory placement [12]. Wu and Chen [22] apply a two-echelon optimal control system to model oil industry economic behavior in the presence of either a single shock or random Brownian shocks. One echelon represents an individual firm, and the other, an aggregation of the industry. Among other conclusions, they find that price and inventory peak after a single shock and dissipate slowly, with dampened propagation to the other echelon. Schmitt et al. [23] study the risk pooling and risk diversification in a single warehouse and multiple retailer supply chain. They show that under a deterministic demand and disrupted supply, a decentralized inventory placement is optimal.

The assumptions and simplifications of analytical work have limited the generalizability of conclusions [24], especially with the complexity introduced by disruptions in supply chains [12]. Qualitative, case-based, and simulation research has complemented analytical work in revealing insights into disruptions issues. Craighead et al. [10] cite as examples of disruption management, recent work on supply chain risks [25], vulnerability [26], resilience [27], and business continuity [28]. They also address a related issue, supply chain severity. Kleindorfer and Saad [29], Knemeyar, Zinn, and Eroglu [30], and Stecke and Kumar [31] provide qualitative frameworks for vulnerabilities and mitigation methods. Sheffi [32] outlines managerial implications of disruptions and risk-management approaches such as buffering, redundancy, and agility as means to achieve resilience.

Another literature stream has focused on simulation-based methodology to study the effects of disruptions in complex supply chains. Focusing on supply-chain design, Klibi and Martel [33] offer a means to simulate disruption scenarios. Disruptions may vary in frequency, location, duration, intensity, and predictability, and may affect both demand and capacity in the supply chain. They recognize a wide range of mitigation activities before, during, and after the disruptions. Schmitt and Singh [34] investigate supply and demand disruptions in a three-stage supply chain, based on base stock practices of a large consumer packaging maker. Their simulation outcomes indicate that disruptions upstream and downstream have differing impacts, and that performance recovery improves with global, rather than local, inventory decisions.

2.2. Expediting

Disruptions represent exogenous shocks to a system, while expediting offers an endogenous means to mitigate through adaptive ordering. Beyer and Ward [35] report that over 65% of orders are expedited in an HP supply chain. Other reported cases of expediting include Amazon [36] and Nintendo [37].

While expediting in production and shipment appears rational as a business behavior, research progress has been hampered by the complexity it induces in modeling efforts [38]. Expediting creates difficulties in analyzing crossover orders not arriving in the sequence they were placed. Analytical research has focused on finding optimal ordering policies at a single echelon. For analytical tractability even in a single echelon, researchers avoid order crossovers by either restricting regular and expedited lead times to differ by one time unit, or assuming instantaneous expedited delivery [39]. Others apply heuristics under more generalized lead times [40]. Using simulation with parameters based on a computer manufacturing application, Levy [41] attributes an increased cost of disruptions to expediting and longer lead times of international supply. Complications of interactions between expedited lead times and capacity have not been considered in the literature we reviewed.

2.3. Bullwhip

Bullwhip effects add realism to studies of disruptions and expediting. With dependencies in material, finance, and information, variations in demand or supply may amplify within and among firms, and disrupt the whole chain [42]. Bullwhip effects have been attributed to both erratic human behavior and rational decision making. Disney and Towill [43], Chen et al. [44], and Chen and Lee [45] provide analytical treatment of rational bullwhip effects under assumptions such as autocorrelated demand for a single product, an order-up-to policy for a single echelon, and no setup cost. This work on bullwhip effects has not considered the impact of capacity interactions.

Sharing information offers advantages in a supply chain, and some authors have addressed this [46,47]. Using simulations of multiple echelons in complex problem settings, Fiala [48] and Chatfield, Kim, Harrison, and Hayya [49] observe the impact of information sharing on demand amplification. In behavioral studies simulated across four echelons, the observed variability is amplified because participants tend to discount information from upper echelons [50] and undervalue pipeline inventory as compared with on-hand inventory and demand [51]. Sarkar and Kumar [52] show different effects of disruptions at the upper and lower echelons. They contrast disruptions at the two extremes of supply chain with or without information sharing. Rong et al. [53,54] observed reverse bullwhip effects due to over-reaction to shared information.

2.4. Order-up-to inventory policy

Policies, which adapt order quantities and frequencies to theoretical inventory levels, are common in practice and have been studied extensively in the literature. Researchers offering analytics and heuristics have been careful in claiming utility only within their system assumptions. Nahmias [55] and Axsater [56] provide details about order-up-to systems, which provide optimality for base-stock policies under certain assumptions about the supply chain structure, shortages, order cost, and demand distributions. Base-stock policies are found optimal over a variety of unimodal risk-neutral and risk-averse objectives in single-item, single-stage systems with multi-period finite horizons and no order cost [57]. Without claiming optimality, order-up-to and other well-known policies have been applied in simple supply chains with supply or demand disruptions [15,17,58].

Finding optimal policies for assembly systems are "notoriously difficult … due to the multidimensionality of the problem" with multiple components and echelons [59]. Benjaafar et al. [59] note that the "literature dealing with optimal control policies for assembly systems is relatively limited." They study a multi-echelon, multi-item assembly system with random demand. Assuming exponential production times and Poisson demand, they formulate the problem as a Markov decision process. A state-dependent base-stock policy is shown to be optimal with respect to holding and shortage costs.

3. A representative simulation model

We study a supply chain structure that offers enough complexity to reflect a realistic supply chain composition, yet small enough to control the experimental environment. The rationale for our choice of simulation methodology, model structure, inventory logic, and performance metrics is as follows.

3.1. Simulation in this problem context

We acknowledge the contribution of Sandia National Laboratories in motivating our field study, methodological approach, and model development. With a sense of urgency after terrorist attacks of September 9, 2001, a group of economists within Sandia embarked on a project to develop a large-scale simulation to assess the regional economic impact of disruptions in critical infrastructure on U.S. manufacturing firms and their supply chains. To investigate vulnerabilities in complex, realistic operating environments, and gain insights about mitigation strategies, they developed an agent model capable of simulating the discrete events of millions of entwined enterprises within regional supply chains, and using enormous computing power, attempted to trace the corresponding economic behavior. These efforts resulted in the development of a simulation-based suite to examine threats and analyze risk assessments for critical infrastructure such as dams, power transmission facilities, and municipal water systems [60–62]. The initial simulation model was developed by us in collaboration with Sandia National Laboratories.

Sandia approached us with an intriguing issue: How to model the macroeconomic impact of a disruptive regional event. The Northwestern United States was chosen as an initial test site for a hypothetical attack. Our role in their modeling effort was to characterize the ordering systems that link procurement, production, distribution, and transportation activities across firms in Pacific Northwest supply chains. Sandia has since incorporated our model findings into studies of the macroeconomic impacts of Hurricane Katrina and the Gulf oil spill [63]. Incorporation of our model recommendations and findings in [60–63] serve as further validation.

Our field work included the aforementioned literature review of related topics as well case studies of three firms. The case studies can be requested by contacting the authors. These cases contributed to developing insights to real-world supply chain structures, performance drivers, complexities, vulnerabilities, and disruption mitigation strategies. The applications motivate a model that is considerably more complex than addressed previously. They help us define a rudimentary but workable model of supply chain activity and operational performance. Considering the complexity of supply chain disruption decisions, a case approach has been used for various studies. Using case studies of eight European companies, for example, Blome and Schoenherr [64] identify strategies to mitigate demand disruptions. They motivate case research as a "good method to study complex phenomenon" such as supply chain disruptions.

With such complexity in this problem context, simulation offers a methodology worthy of consideration. Concurring in this assessment, Snyder and Shen [12] observe that "disruption models are generally much less tractable than their deterministic-supply counterparts and require numerical optimization since closed-form solutions are rarely available." The authors propose simulation as an alternative to analytical study "to gain insights using realistic models rather than to find optimal solutions to exact but vastly simplified models." Snyder et al. [16] motivate the use of simulation as a "natural tool for evaluating the impact of disruptions in … a supply chain." Chatfield et al. [49] reinforce this by noting, "simulation modeling of supply chains can provide both realism and utility … by accounting for the natural variations that occur in the various processes within the supply chain, and that could not be captured analytically."

3.2. A Reasonable baseline for the supply chain structure

We model more complex supply chain structures, order interactions, and mitigation tactics than we found in the literature, although we draw specific elements from our field work and from several papers by others to develop a representative model and establish its parameters. Our three case firms make electronic products ranging from consumer appliances to devices used by original equipment manufacturers. To gain insights into supply chain behavior, we interviewed personnel from these three representative firms and some of their suppliers. The three firms are disguised as INT, ABC, and XYZ, and the cases are summarized in Table 1. The three supply chains involve multinational interests that broaden the exposure to disruptions. Most electronic components are internationally sourced with associated transportation exposure throughout the extended supply chain. Some electronics assemblies are embedded into larger systems made by such customers as Boeing and Honeywell, who, in turn, export many products.

Our field and background research suggest that a four echelon structure with assembly provides a useful representative baseline for modeling an industrial supply chain. In particular, the supply chains in all three case applications support four echelons with component assembly. Most of the aforementioned simulation research on bullwhip effects covers four stages to adequately represent demand amplification. Other supporters of a minimum of four echelons include Juneja and Rajamani [65], who cite an electronics supply chain with assembly that includes the principal components of Selectron (supplier), Matsushita (manufacturer), Panasonic (distributor), and Best Buy (retail customer). Swaminathan et al. [66] propose multiple echelons and assembly as key model components, in the context of an agent model. We concur on the advisability of including assembly, regardless of the industries represented. Whether at home, in an office, in a vehicle, or in a factory, one typically encounters mechanical and electronic assemblies comprised of two or more components.

Fig. 1 shows our rudimentary supply chain model. Each echelon requires activity and storage. At Echelon 1, products are ordered and shipped to a local or distant customer, which might be an OEM manufacturer, distributor, or retailer. Echelon 2 represents assembly of components A and B into finished goods. In Stages 3A and 3B, suppliers (internal, local, or distant) transport parts, or fabricate prior to transport. Stages 4A and 4B represent transportation and storage activities of domestic or overseas distributors. Fig. 1 also displays lead time parameters in days – lead times (LTs) under normal operating conditions and expedited lead times (ELTs). These reflect the times of production and delivery, and are based on the cases and the literature. Note that some researchers also consider the end customer as another supply chain echelon. This interpretation increases the number of echelons in our supply chain model to five. We next review the inventory logic, with details in Appendix A.

3.3. Inventory logic

Supply chain ordering systems regulate the goods flows and inventories across companies in a supply chain. Our system assumes stationary, autocorrelated demand at Echelon 1. Each echelon/stage observes only the demand it receives from its immediate stage customer. Using historical demand from the immediate customer, we forecast at every stage for each successive period the mean and variance of demand using single exponential smoothing, a method used by many companies [24].

The demand and variance estimates are applied, along with a service-level parameter, in a single-stage order-up-to formula to update the replenishment order quantity each period. Replenishment orders at one stage shown in Fig. 1 become the demand at the preceding stage. Inventory balance equations link each stage in a periodic (daily) review system. Each stage follows this FIFO logic each day: (a) launch a replenishment order if necessary using the dynamic order-up-to system, (b) withdraw this day's demand from available inventory to initiate shipment to a customer, (c) receive goods from the previous stage into inventory, and (d) update the inventory or backorder quantity (where backorders are permitted).

If the demand at the succeeding stage is more than the available inventory at Echelon 1, we assume a partial shipment, with the rest lost. Prior to assembly at Echelon 2, inventory of the two component types is maintained, and orders are placed if warranted. The quantity of an assembly order cannot exceed the available inventory of either component. At Echelons 2, 3, and 4, shortages are backordered. This is motivated by the practices of all three case firms, who experience lost sales with unfulfilled demand from their customers, and backorders with suppliers in accord with long standing relationships. Other approaches have also been applied in practice (e.g., see [47]), and the system behavior may well be affected by assumptions of how shortages are handled.

The parameters used in demand generation, forecasting, and inventory control are presented in Appendix A. The order logic assumes periodic review with no setup or order cost, infinite production rates, fixed lead times, and i.i.d. demands. While suitability of order-up-to policies is by no means assured for our system, this logic is the most robust and applicable of available methods. Attributing to their popularity, all three case companies use periodic time-phased order-point systems (ERP). A considerable amount of literature has been devoted to this applicability.

3.4. Performance metrics

There are many ways to measure the short and long term effects of disruptions and corresponding mitigation [10]. We focus on a few first-order process metrics concerned with tactical response and recovery [67,68]. We apply three process metrics frequently cited in the literature as performance drivers and applied in our case supply chains to capture important economic effects during and after disruptions. The first is the *service level* (fill rate) experienced by customers at the final supply chain echelon. Disruptions in production and transportation may reduce product availability to customers, and in turn, affect second and third order performance metrics such as profitability, market share, and reputation. At the final echelon, customers such as retailers and OEMs may have other supply sources, and shortages may be lost to these sources. Some may have contractual arrangements that might instead specify backorders. The opportunity costs of shortages from either lost sales or backorders that reach the final echelon can be severe, with loss of future business at stake. For example, late delivery of avionics to Boeing Commercial, an OEM customer, may in turn cause late delivery of an aircraft. This would result in loss of interest on delayed revenue receipts of hundreds of millions of dollars, diminished revenue arising from contractual penalties, and loss of goodwill with the airlines.

Firms at intermediate echelons typically have long term relationships with customers that call for backordering noncommodity items [47]. Countermeasures such as expediting and inventory positioning enable some of these backorders to catch up in subsequent stages. Companies at various supply chain stages often respond to disruptions with premium transportation and alternate sourcing [69,70]. Nevertheless, this *system expediting* may introduce significant premiums for transportation and production that drain profit margins throughout the supply chain. Expediting is our second metric.

The third process metric, *system inventory*, also drains profit margins. Well-positioned inventory, however, may provide a safety net against disruptions, and decrease shortages and expediting. We chose total supply chain inventory as a metric because

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Table 1
Case summaries.

		Firm INT	Firm ABC	Firm XYZ
Supply Chain	Model	A 4-echelon supply chain with assembly is sufficiently representative.		
	Supply chain span	Global spread with overseas transport, and distribution centers located elsewhere in the US, some local suppliers, and customers ranging from local to overseas.		
	Finished products	60 models with over 2500 configurations	200 different finished product types	Three product groups, each that includes a lot of customization
	Primary customers	Manufacturers, distributors, and retailers	Automotive, utility, military, and aerospace industries	Aerospace OEMs
	Sole sourced components	Approx. 10%	Approx. 20%	Approx. 20%
Operating policies	Operation-type	Assemble-to-order	Make-to-order	Primarily make-to-order
	Electronic Co. operations model	Lean JIT system using visual controls and Kanban for internal processes. MRP ordering for externally sourced components.	Toyota style JIT for internal processes. MRP ordering for externally sourced components.	MRP ordering internally and externally.
	Management issues	High product variety, high inventory and overhead costs, and delivery problems	Expectations for high customer service	Product cost and delivery performance
Risk management	Concerns	Telecommunication/power failure, transportation accidents, and sole sourcing		
	Recent disruptions	Power failure, transportation accident. Sole source disruption	West coast port lockout	Texas port closure. Land-line service failure
	Notable consequences of disruptions	Electric power vulnerability. Loss of sole-source supplier may introduce delays of up-to two years.	Better equipped than the other two because of lesser number of SKUs. No telecom backup for contingency plans.	Vulnerable to power and telecommunications failure. No backup generator or contingency plans.
	Mitigation planning	Buffering. Expediting. Basic preventive measures such as fencing, guards, and lighting.	Buffering. Expediting. Alternate sources and routing. Backup generators.	Buffering. Expediting. Alternate sources for most components. Geographically dispersed locations.

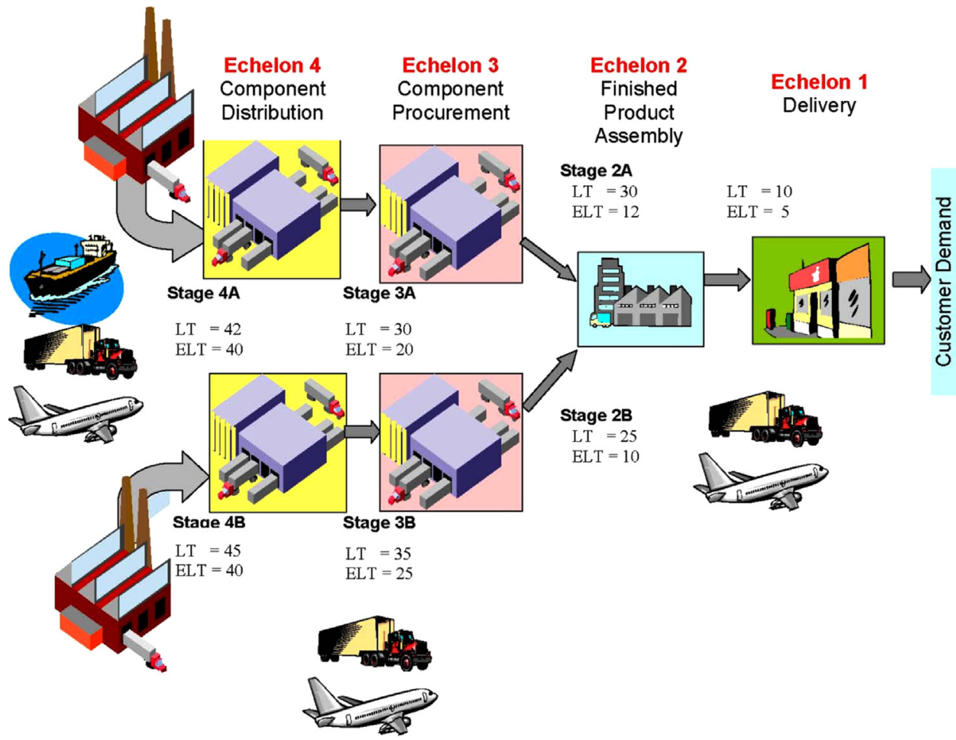

Fig. 1. Prototypical supply chain.

without accountability, inventory in motion or at rest might be shifted elsewhere, and associated costs overlooked. Beyond the case applications, similar service and inventory metrics are commonly observed in much of the literature we reviewed, and expediting metrics have an important role in some of the work on post-disruption mitigation.

We show in Key Issues 1 and 2 in Section 4 that performance dominance among process metrics in our simulation results enables us to reach general conclusions without rolling up metrics into total costs. Schonberger [67,68] has found that measures such as total cost and profit are once, twice, or more removed from the first-order process drivers that are easily measured, understood, and acted upon. In other instances (Key Issues 3 and 4), we find it necessary to weight the process metrics, and elaborate on how the cost parameters are justified and applied.

4. Experimental results

Simulation runs were conducted using the aforementioned model structure and metrics, and the experimental design was tailored to examine each of the Key Issues 1–4. Cost structures varied substantially by firm and item in our case firms as well as in other research. We addressed this complication in ways that differ by key issue. We wish to examine the performance effects of disruptions without adaptive ordering interventions in Issue 1, and with expedited ordering in Issue 2. We avoid the need for cost estimation by applying common practices of ordering to attain service level criteria. See Appendix A for details. With these Issues 1 and 2, we apply MANOVA across process metrics, and focus on general statistical inferences consistent among the metrics. See Appendix A for a discussion of MANOVA.

With Key Issues 3 and 4, however, weighting the metrics allows us to depict different cost structures. This also enables us to examine the collective effects of dynamic cost-based ordering policies and global cost search methods as an alternative to expediting interventions. One example that demonstrates ill-behaved cost performance is presented in Issue 3, and this phenomenon, which challenges traditional tractability assumptions, is supported in general in Issue 4 with statistical analysis over a variety of cost structures.

4.1. Key issue 1 – system performance with a disruption

Management of all three case firms indicated that the “duration of a disruption” is a critical factor, and expressed concerns about response and recovery. They had encountered disruptions of fire, weather disasters, worker strikes, port lockouts, supply shortages, power failures, telecommunication failures, transportation breakdowns, and machine breakdowns. In one example, the loss of a sole-source supplier introduced delays of up to two years to find and procure alternate materials. In another, a disruption in the transportation of commodity components, with replenishment by sea, involved a 90-day delay. Loss of electric power or telecommunications would quickly stop activities in every firm in a region during the length of the disruption, although essential telecommunication transactions might be handled by cellular telephone, if the networks are not overloaded. Contrary to previously cited research on information sharing in supply chains, managers of the case firms warned that quality information is sparse during a crisis, even within progressive supply chains. One would not likely know how other customers and suppliers will behave during a disruption, and when the disruption will end.

Consequently, we chose to introduce a generic shock (time delay) to represent many types of disruptions that may occur in practice. We limit information sharing such that each echelon only has access to demand information from adjacent lower echelons. After an initialization period of 1000 days, we induce a 20-day disruption, and compare performance thereafter with the base case (without expediting and disruptions). Clearly, the time elements are interrelated. For our experiments the review period is one day, a short period relative to the disruption, and the run length is relatively long, i.e., 2000 days. Issues of simulation steady state and statistical independence are explored in Appendix A.

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In practice, disruptions may occur at any stage of a supply chain and cause complex interactions elsewhere. In our exploratory research, we limited the disruptions to each end of the supply chain: Echelon 1 (shipment to customers) and Echelon 4/Stage A (supply by a parts distributor). During each disruption, the facility at the affected echelon receives shipment orders in-route before the start of the disruption, but stops all other activity. It cannot place orders, produce orders, or make shipments. A similar approach is used by Sarkar and Kumar [52] to study the behavioral effects of disruptions at upper and lower echelons. However, their study used a traditional beer game model and did not have an assembly stage.

For Key Issue 1, performance is observed on a day-by-day basis over 100-day time blocks, experiments are replicated 100 times, and performance is compared between the disrupted and base cases. A time block covers five months in a 240-working day year. We chose 100-day time blocks after observing the behavior of our process metrics within blocks of various lengths. We found 100-day blocks short enough to capture significant performance effects, as we next show. Shorter disruptions than ours may warrant shorter blocks to reveal after effects.

Our MANOVA design has two fixed factors: time block and location of disruption. We do not mitigate with expediting for this Key Issue, and observe the service-level and system-inventory metrics as dependent variables. We find that values from each metric are drawn from different distributions, according to Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root statistics at the .01 level [71]. This enables us to separately consider each metric (see Appendix A). Results for the two metrics are summarized in Fig. 2. Each point in the graphs depicts the mean value over an indicated five-month time block.

Waller-Duncan multiple-range post-hoc tests disclose that regardless of the location of disruption, service level is significantly different between the disrupted state and base-case state over the first two time blocks (10 months). In the final eight time blocks, there is no significant difference among the means and zero. All of these results hold at the .01 and .05 levels.

System inventory is significantly different over the first five time blocks (25 months) with both disrupted locations. In the final five time blocks, there is no significant difference among the means and zero.

Clearly, the effects of disruptions on the two performance metrics last a long time. There are severe decreases in service level for almost a year. Additional system inventory over the base case exceeds ten weeks of demand for more than two years after a disruption at Echelon 1. Fortunately, the direction of these first-order process metrics support one another, and our general conclusions that the disruptions last a long time are not dependent on specific cost parameters applied to the two metrics.

We performed additional analyses comparing disruptions at Echelons 1 and 4 (as disclosed by contrasts between means in left and right graphs). The MANOVA contrasts at the .01 level indicate significantly worse service levels at Echelon 1 than 4 over the first five months, as well as increased system inventory (more than twice the amount) in months six through 25. Recognition of a disruption at Echelon 1 is transmitted to other echelons as a function of the smoothing parameter α, the service level parameter, and lead times. Even with small α values, the forecasted demand at subsequent echelons drops fast, which reduces the order-up-to levels and order quantities. This amplifies as the variability propagates across echelons from Echelon 1 in accord with lead time offsets, a finding also observed by Chen et al. [72].

By contrast, a disrupted facility at Echelon 4 immediately suspends production and shipments to Echelon 3, but the interruption in supply goes unnoticed in our system, i.e., until shortages eventually appear as lost sales at Echelon 1. Beforehand, shifts occur from inventories to backorders at Echelons 4, 3, and 2, but the pipeline totals remain stable, and so do the order-up-to levels, demand forecasts, and order quantities.

We observe a strong whipping effect across echelons, especially with a disruption at Echelon 1, and these results are supported by much of the bullwhip literature, e.g., [42–44,72]. Chen and Lee [45] and Disney and Towill [43] derive bounds on demand amplification whose volatility grows at stages away from echelon 1. These

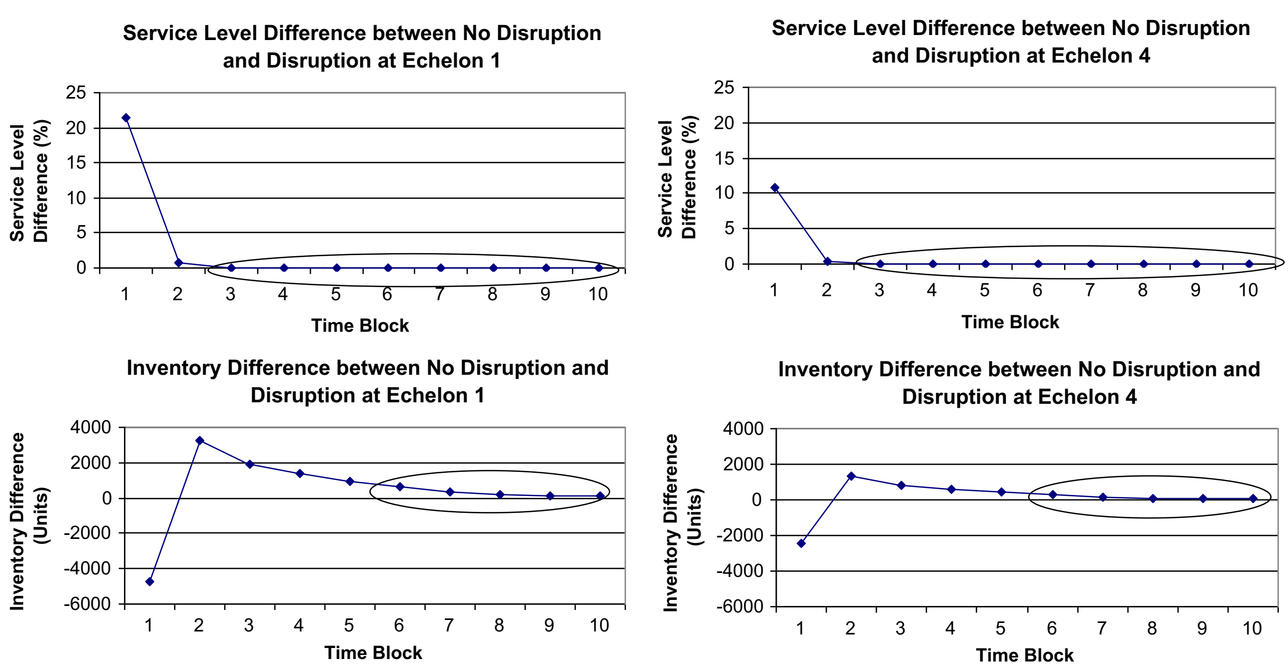

Fig. 2. Performance effects of a disruption. [Each point represents a mean value over a time block. Waller-Duncan multiple range tests indicate that points not circled are significantly different from one another; those circled indicate no significant difference between one another and zero. These results hold at the .01 and .05 levels. The table presents data when no disruption mitigation, using expediting or adaptive ordering strategy, was used.]

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references also contain tables and figures illustrating bullwhip from experimental data [43] and industry data [42].

However, these other results are inconsistent with the findings by Wu and Chen [22], who noted that regardless of source in a two stage system, larger fluctuations occur closer to the disruption and dampen when propagating away. We attribute this to differences in our forecasting and ordering system, which includes more than two echelons, the presence of lead times, price inelasticity, and limited information sharing.

Inventory policies, stage lead times, and the length of a disruption may affect the ability of a supply chain to absorb the impact of a disruption at Echelon 4. For example, when experiencing a disruption duration longer than we considered, the buffer in the supply chain may not be enough to mitigate the disruptive effects. In such cases, buffer inventory may only partially mitigate the disruption, and lower echelons may experience shortages. Additionally, performance differences may arise when lead times are shorter than we considered, e.g., with lean inventory practices even more effective than those practiced by our electronics case firms. As another example, longer disruptions at Echelon 1 could further exacerbate bullwhip effects and cause further deteriorations in supply chain performance. Following the bullwhip literature and our findings, however, we would expect in general that the performance impact of longer disruptions (than we considered) at Echelon 1 to be costlier and longer lasting than disruptions of the same length at Echelon 4.

The bounds of Chen and Lee [45] show impressive potential savings from information sharing in the supply chains, but research findings are mixed as to how to systematically incorporate information for performance advantage [48–51,53,54]. The precise effect may be affected by the manner in which information is shared and used in altering ordering decisions. Information quality and trust within the supply chain may also affect the impact of disruptions. Overreactions at echelons other than 1 to information about disruptions might increase system variability and costs, despite the supply chain inventory. Some have observed these reverse bullwhip effects due to information sharing and over-reaction [53,54].

Our experimentation sheds light on the relevance of Key Issue 1 and offers novel, situation-based insights about the propagation of disruptions within the context of our parameters. We describe in Appendix A the care with which the lead times were selected. However, we acknowledge that the effects of disruptions across echelons might be affected by the lead times between them, the duration of the disruption, and the manner in which information along the supply chain is treated. This suggests further research on the reactions to and effects of disruptions at different stages in the supply chain under a variety of experimental conditions.

4.2. Key issue 2 – system performance under expediting

All three case supply chain firms frequently use expediting to avoid shortages. Depending on the echelon, the percentage of orders expedited ranges from 5% to 20%, with a premium cost per unit ranging from 10% to 50%. Expediting is typically accomplished using faster transportation options, or with production adjustments such as overtime, additional shifts, part-time help, alternate routing, and outsourcing. Bradley [73] provides additional motivation for expediting.

Following prior practice and research, we applied two triggers to expedite lead times as orders are launched. We experimented with a range of parameters for each type of trigger to match an expediting frequency observed in the case studies. The first trigger is activated when the quantity throughout the stage pipeline (on-order plus on-hand inventory) falls below the expected lead time demand [40,74]. The second is activated when on-hand inventory falls below a demand-based target. See Appendix A for details. Expediting (which might be due to a reduction in production and transportation times) shortens the total lead time between echelons. Beyer and Ward [35], for example, observed that Hewlett Packard's supply network applies this second type of trigger to expedite via air transport.

We compare the performance results of cases with and without expediting. If the expediting option is enabled, expediting is permitted at all echelons, with order crossover a possibility. We replicate 100 times and are able to consider separately the three performance metrics (final-echelon service level, system inventory, and system expediting) as dependent variables. This is because values from the three metrics are drawn from different distributions at the .01 level according to the Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root statistics.

We find significant performance differences at the .01 level between the base and expediting cases for each metric. These differences raise issues about the value of expediting. Shortages improve with expediting by only .18 units per day on average demand of 111 units, while total system inventory increases by an average of 787 units per day (almost seven days of average demand). System inventory increases so much because expediting increases the variability in order quantity and frequency, and this variability is amplified elsewhere in the supply chain. Since all three first-order process metrics deteriorate with expediting, these conclusions do not rely on values of cost parameters that might be applied as weights.

An explanation for the poor performance of expediting versus dynamic ordering might be traced to underpinnings of each. Our dynamic ordering scheme relies on frequent parameter updates within a static ordering policy. Static order-up-to policies and forecasting models each have robust theoretical and analytical roots for single stage systems [55,56]. In our more complex multi-stage system, changes in the dynamic order-up-to quantities are likely gradual, and the corresponding system variability more controlled. This is because of the discounting of current and historical information that occurs in the forecasting procedure. By contrast, our expediting rules, as others before us, rely on the current state variables, but lack historical perspective. They do not filter, nor dynamically adapt to, demand volatility.

According to the personnel we interviewed, expediting offers a first line of defense against shortages, but our findings raise questions about the value of this practice as a mitigation approach of choice. We are not the first to raise these concerns. Even before bullwhip effects were recognized, the practice of expediting was challenged because of the nervousness it induces in MRP systems. See Schmitt [75] and its citations. In addition, expediting, while considered necessary [73,76], is usually expensive [74,77]. Beyer and Ward [35] observed that expediting by air in HP's supply chain costs up to five times more than standard shipment by sea. In our field applications, we found that expediting was quite expensive as well.

Three case companies motivated our choice of parameters of lead times and expedited lead times. In general, the performance effects of expediting may be affected by the extent to which orders are expedited. Instantaneous, or very short delivery (relative to our state of normal), may be helpful in significantly improving service levels, and also help in terms of system inventory and order variability. We suggest further experimentation to investigate issues of generality beyond the conditions reflected by our case applications.

Despite evidence of the undesirable consequences of expediting, we do not expect firms to discontinue this practice. At an assembly echelon, for example, it would be difficult to convince managers of an electronics firm not to expedite one component, when the remaining hundreds needed for assembly and sale of a finished product are available. Practitioner behavior might be influenced by future research that finds merit in the targeted application of certain types of expediting at specific supply chain stages, or between stages. In addition, information sharing across echelons may help reduce the unintended consequences of expediting, but there is little evidence of this in the literature. Because of bullwhip properties, overreactions to current information might adversely affect future system performance [53,54].

4.3. Key issue 3 – system performance with dynamic order policies – applicability of analytics and heuristics in the parameter search

Ross et al. [58] found instances where a non-stationary time-varying order-up-to policy is more effective than a static policy in terms of the total costs of holding, ordering, and lost sales. An issue arises for us as to how to find reasonable cost-based order-up-to levels across multiple echelons in the presence of demand amplification. As an alternative to expediting interventions, we explore in Issues 3 and 4 the potential reactive capabilities afforded by improved estimates of dynamic order-up-to parameters across echelons. Here we use traditional formulations for calculating order-up-to levels that rely on cost rollups, and allow these levels to vary across periods.

We observe non-unimodal total cost behavior within a range of stage order-up-to levels, while leaving the inventory systems unhindered by expediting. To define a case, we chose a holding cost of $1/unit/day, a backorder cost of $2/unit/day (at Echelons 2, 3, and 4), a lost-sales cost of $3/unit (at Echelon 1), and a stage production/transportation cost of $1/unit. We present the notable erratic behavior for this one case, which highlights the potential savings of good parameter estimates. In the next section (Issue 4), we observe similar erratic behavior in total cost under a variety of cost parameter combinations.

Fig. 3 shows plots of the simulation results of total cost over various stage order-up-to levels for this example. The two graphs to the left focus on behavior solely at Echelon 1, while the ones to the right show interactions between Echelon 1 and Echelon 2.

The graphs on the left show total cost values for discrete order-up-to levels at Echelon 1, while allowing the other three echelons to derive order-up-to levels from stage demand forecasts. The top left graph displays total cost performance versus Echelon 1 order-up-to levels over the range [1,2000]. Clearly, the local optima vary considerably in value, e.g., one yields a total cost 6.95 times larger than the lowest observed total cost value, given the starting point. The bottom left graph depicts a finer grain relationship over the range [1000,1530]. It highlights the striking volatility of the cost function.

The graphs on the right of Fig. 3 show the interactive behavior between the first two echelons, depicting total supply chain cost while varying Echelon 1 order-up-to levels for prescribed Echelon 2 levels. In this set of experiments, Echelons 3 and 4 derive order-up-to levels from stage demand forecasts. The course and fine grain representations at the top and bottom right, respectively, generalize the previous observations solely about Echelon 1. Clearly, computationally-efficient iterative line searches or analytic searches can yield poor solutions in these operating scenarios, depending on the starting point.

There are multiple ways to confirm concerns about ill-structured performance behavior and inappropriateness of exact approaches. Some involve violations of Kuhn-Tucker conditions, or alternatively, properties of derivatives. We chose another way, the presentation of a counter example, one where an exact approach yields higher total cost. While the cost parameters are realistic in

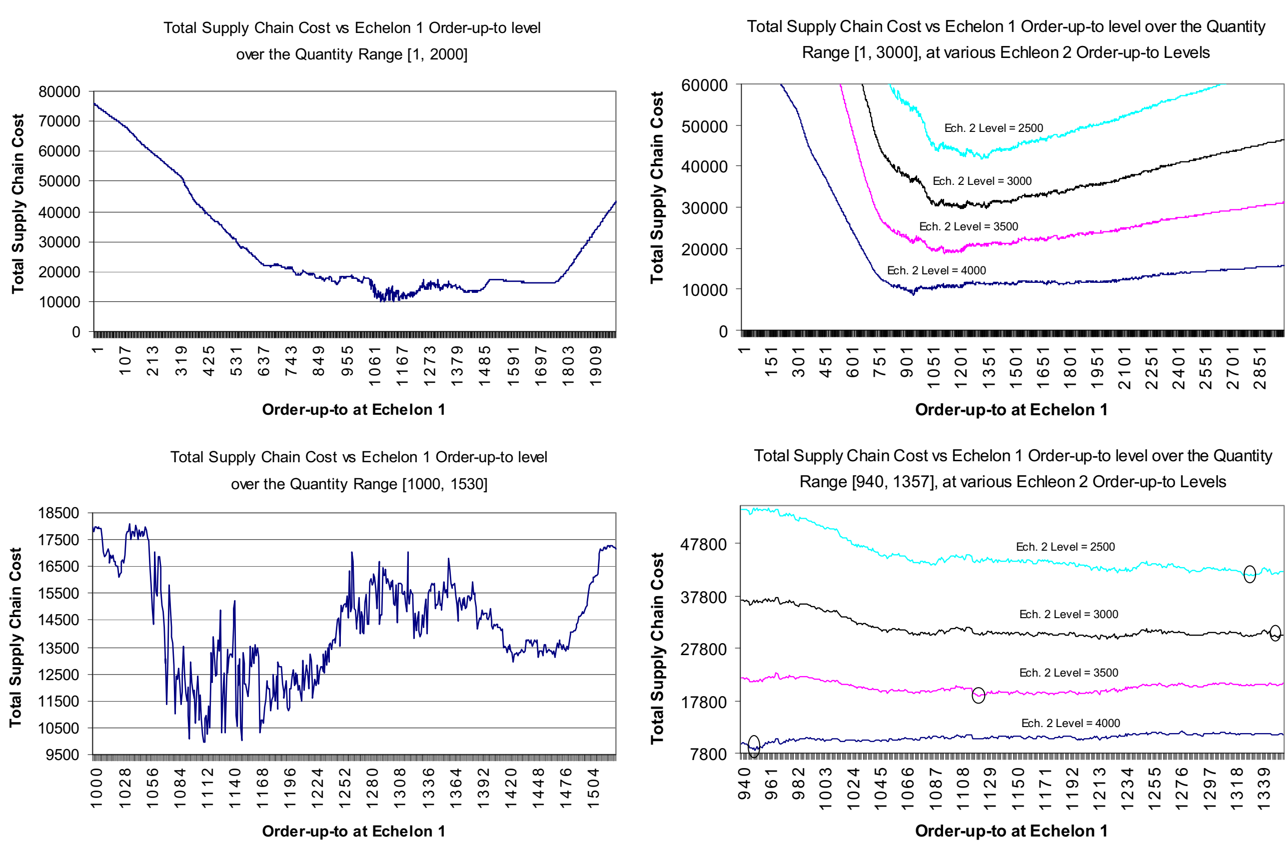

Fig. 3. Shape of total cost function. [Total Supply Chain Cost while Varying Echelon 1 Order-up-to Level; Three Other Echelons Derive Order-up-to Levels using Demand Forecasts. Total Supply Chain Cost while Varying Echelon 1 Order-up-to Level at prescribed Order-up-to Levels at Echelon 2; Other Two Echelons Derive Order-up-to Levels using Demand Forecasts].

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that they are within limits of most prior studies we examined, the existence of such a counter example, with parameters of any magnitude, is sufficient to obviate generality of exact analytical approaches that assume unimodality. In the next section, we examine the relative efficacy of unimodal and global search methods over a wide variety of cost structures.

4.4. Key issue 4 – global search versus line search

With insight from the preceding key issue, we examine the modality of the objective function surface across different cost settings. In their agent model simulation, Sandia applied a standard genetic algorithm (GA) utility as a means to "jump over" local optima in a global parameter search across echelons. Taking this further, we conducted experiments to evaluate GA methodology as a global optimizer in our problem context. Besides Sandia, the GA tool developed by us has been applied to optimization of the satellite tracking and monitoring application. As the review begins for each period in the planning horizon, GA considers the history to date to conduct a search for cost-effective order-up-to quantities across all echelons and stages. The GA utility represents candidate order-up-to solutions as binary numbers in the search. A randomly generated set of 100 solutions initiates the search procedure. Crossover and mutation operators are used to overcome local minima. At an iteration, two of the 100 solutions are randomly chosen for crossover, with a small probability that the binary solutions would mutate. The solutions generated after crossover and mutation are tested for fitness based on total supply chain cost. Using a GA 'elitist' strategy, the 100 best solutions are preserved and used as candidate solutions for the next iteration. For details, see [78].

Using a single inventory echelon, Snyder and Shen [12] found the total costs of inventory, orders, and backorders fairly well-behaved, and employed line search (LS) to establish (s,S) parameters. We also use LS as a basis for procedural comparison and modality concerns. LS ensures optimality only when the objective function is unimodal. In our problem setting, an LS approach that increments upwards from an order quantity of 0 to find a local optima typically yields much higher costs than GA. To facilitate a reasonably fair comparison, our adaptation of LS searches one echelon at a time, beginning each period with an order-up-to quantity equal to the mean lead time demand at Echelon 1. It searches each direction in the neighborhood (upward first) until it encounters local optima. It allows demand forecasts to guide decision making at other echelons. While holding the order-up-to parameter fixed at the local optimal level at Echelon 1, the search process continues echelon by echelon until parameters for both stages of Echelon 4 are determined. In pilot experiments, this adaptation of LS resulted in much better solutions, while keeping computation time reasonable.

To represent a variety of operating conditions, we selected a range of cost parameters as presented in Table 2. We considered findings from the literature in the context of our research objectives. Relative costs depend on the type of product, industry, and supply chain, among other factors. Cohen et al. [76] observed that with short life cycles and obsolescence in the semiconductor industry, the cost of losing a sale is about twice the cost of backlogging. Faaland et al. [79] experimented with lost-sales costs in a single echelon ranging from 62 to 500 times the periodic inventory holding cost, shortage values much higher than the ones we chose. Their parameters were based on a cross-industry survey by Boer and Jeter [80]. Our motivation in the choice of relatively low shortage costs is to compare a GA global optimizer and LS under modest conditions. We observed in pilot experiments that larger shortage costs relative to inventory carrying costs further exaggerated differences between solutions obtained by the GA and LS approaches. This suggests our conclusions are insensitive to shortage cost values.

Table 2
Various costs at two levels each.

	Back-ordering cost	Cost of lost sales	Carrying cost	Expediting cost
Low	4	6	2	3
High	8	12	4	5

Table 3 shows the savings under various cost scenarios. The percentage improvements represent averages over 100 replications for each of the 16 cost combinations. The superiority of the GA global optimizer over LS holds at the .005 level using student-*T* tests. The solutions obtained by global optimization as compared with those obtained by LS yielded a cost savings greater than 16%, and in one scenario greater than 30%. Less effective starting solutions for LS would have made the relative differences between the approaches greater.

In single-stage stationary systems, even with deterministic demand, tractability has not been established when shortages are lost [81]. Others have acknowledged but discounted this phenomenon by asserting that the total cost surface is relatively flat in regions around the global minimum. We question this conventional wisdom by showing how far off the local optima may be under a broad spectrum of cost parameters. The literature on disruptions, expediting, and bullwhip effects express similar concerns. We claim applicability of this modality phenomenon only within the limits of our supply chain structure and parameter settings, and further experimentation seems warranted.

We acknowledge the potential for practical contributions in addressing the global optimization problem. However, our use of genetic search for this purpose achieved its improved cost results at a computational price. Each run consists of successive parameter updates for 2000 periods, replicated 100 times. On a laptop with Intel Core i5 processor, the time per run for GA was about 14 h, and our adaptation of LS averaged about 10 min. While the computation time for GA may be acceptable for Sandia with its fast complex of computers, we recognize an opportunity in future work to employ metaheuristics such as tabu search and scatter search that have proved superior to GA in global optimization, as disclosed in recent studies [82–85].

5. Conclusions and future directions

Disruptions can have many sources covering the gamut from natural to accidental to intentional. Regardless of cause, disruptions can have long-lasting, widespread, and costly effects on supply chains. We describe aspects of a stream of research to assess several key issues concerning the economic impact of supply chain disruptions. We consider simulation with embedded adaptive ordering analytics to augment the optimization models of others whose utility may depend on the validity of inherent simplifying assumptions. This enables us to relax customary assumptions such as aggregation of demand and supply data, substitutability of supply options, independent and steady-state behavior of underlying stochastic distributions, well-behaved objective functions, and simple supply chain structures. Our study was initiated to address Sandia's concern that entities within the U.S. government and private sectors cannot afford to wait for researchers to overcome the substantial challenges of relaxing the underlying assumptions in optimization models, given the high stakes that are involved in disasters.

Drawing from cases and other literature, we offer a fundamental set of design requirements, performance metrics, and

Table 3
Results for line and genetic search under various cost combinations.

Back ordering cost	Cost of lost sales	Carrying cost	Expediting cost	Line search LS	Genetic search GA	Reduction in cost LS-GA	Mean percentage cost savings
Low	Low	Low	Low	5510.1	4723.8	786.3	14.27
Low	Low	Low	High	6067.8	4936.1	1131.7	18.65
Low	Low	High	Low	8085.5	6857.9	1227.6	15.18
Low	High	Low	Low	6212.2	4969.1	1243.1	20.01
High	Low	Low	Low	6906.1	5169.8	1736.3	25.14
High	High	Low	Low	7642.2	5442.6	2199.6	28.78
High	Low	High	Low	9966.2	9226.6	739.6	7.42
High	Low	Low	High	7428.0	5241.3	2186.7	29.44
High	High	High	Low	10,287.1	9276.9	1010.2	9.82
High	High	Low	High	7976.2	5510.8	2465.4	30.91
High	Low	High	High	9946.1	9225.6	720.5	7.24
Low	High	High	High	9742.1	8963.6	778.5	7.99
Low	High	High	Low	8732.9	8124.1	608.8	6.97
Low	High	Low	High	6683.2	5102.8	1580.4	23.65
Low	Low	High	High	8520.2	8330.0	190.2	2.23
High	High	High	High	10,711.1	9412.3	1298.8	12.13

research questions. Our findings lead to the conclusion that a representative model should include at least:

- Four echelons per supply chain
- One echelon with assembly
- Bullwhip effects facilitated by a multi-echelon inventory system with local planning
- Shortages along the supply chain in the form of backorders and lost sales
- Capability to expedite at all stages
- Three metrics as performance drivers (service level at the final echelon, system expediting, and system inventory)
- Disruptions in the form of time delays at various stages in the supply chain.

Each design element is anchored with citations from papers, which span many industries and operational settings. Additionally, our field work on actual cases was crucial in weaving all of the elements together into a coherent problem context, as a precursor to model development.

Guided by these design elements, we explored research questions, whose answers were driven by simulation results. This led to the following additional key findings.

- Lost sales, multiple echelons, and assembly serve to perturb the stationary behavior that has otherwise been assumed in less complex systems. Disruptions and expediting exacerbate the situation.
- Variability from disruptions is amplified across the model structure presently considered, and has long-lasting and costly consequences particularly when the disruption source is downstream and close to ultimate consumption in the supply chain.
- Standard industry practices of setting order parameters locally and intervening with expediting contribute to system variation.
- Dynamic determination of inventory parameters globally across echelons offers substantial promise of mitigating these undesirable effects without special intervention. Additional research is needed to streamline the parameter search process.
- Although increased information and flexibility to react are generally appealing, it is also easy to overreact, with undesirable consequences. If local planning is applied, as is often the case, we recommend that current demand information, with its inherent variability, should be discounted substantially especially towards the supply end of the chain. Pilot experimentation prescribed a low smoothing weight of .01 on the most recent local information for the firms in the last echelon, Echelon 4. A disruptive event creates a critical watershed. The issues are how much weight to place on the news and what to do about it.

The remainder of the section considers the implications of such ill-behaved cost performance in a four-echelon supply chain. Our investigation reveals a weakness of analytical optimization approaches in the present setting by providing a counter example where these methods are unable to obtain satisfactory solutions. Results of this one case are further supported by statistical evidence in experiments over a wide range of cost structures. Our cases, model development, and experimentation highlight the value of simulation analysis and field study as means to verify key propositions, including those that indicate the severity of a disruption is related to time, its location, the structure of the supply chain, and types of mitigation. This buttresses assertions by Craighead et al. [10]. By further extension, we address disruptions at each end of a four-echelon supply chain, and find that inventory cushions the disruptions occurring upstream. This suggests that an expanded study may benefit from investigating disruptions at intermediate echelons as well.

The irregular cost surface documented by our results leads us to observe that future efforts should be directed towards developing efficient and effective search methods to find local optima close to global cost values. Research in improved metaheuristics for global optimization should provide means for obtaining better solutions to supply chain problems and for doing so efficiently. This work has an important intersection with analytics through the use of data mining in simulation and optimization, as noted in Better, Glover, and Laguna [86]. From a managerial perspective, case firms such as those we studied, which employ interconnected periodic-review time-phased order-point systems (ERP), may be able to collaborate on dynamic ordering policies when provided with appropriate decision support tools.

The three cases contribute insights to prior case work on performance metrics, and help to define a basic workable model. Our conclusions are bound by assumptions and based on consistent practices of these case firms. Lost sales are assessed at echelon 1, and backorders at all other echelons. An exploration of other assumptions about shortages at various echelons might yield interesting insights. With fixed and known replenishment lead times, periodic review, and iid customer demands, Janakiraman et al. [87] compare two single-stage inventory systems, one with shortages lost, and the other with shortages backordered. The relative performance of their system under the two alternatives varies in complicated ways in instances where the unit lost sales cost is higher than the unit backorder cost. A higher unit cost for lost sales is reasonable since backorders delay contribution-to-

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profit, while lost sales eliminate it. Future research that covers various assumptions about shortages may add insight, especially in the presence of multiple echelons and bullwhip effects. Consider, for example, the application of lost sales, instead of backorders. We suspect that on one hand, system stability would benefit from the reduced mean demand from lost sales, but on the other, truncated (lost) demand might induce additional variability to be amplified at other stages.

Sandia has extended our model to include price/demand elasticity functions, and a diverse customer base for agent firms. Others have suggested the need to capture the economic effects of product quality, resilience, and preparedness [10]. As a means to supplement our examination of normal and expedited activity lead times, it might also be worthwhile to consider capacity interactions resulting from finite replenishment, setups, and capacity adjustments (e.g., overtime, additional shifts, part-time help, alternate routing, and sub-contracting). Non-stationary demand, stochastic lead times, stochastic failure times, lead time/demand elasticity, and a range of lead times and disruption durations are other realistic extensions. Each of these extensions would have introduced considerable complexity into our experimental design, and we chose to limit the scope. We used expediting triggers based on pipeline inventory and on-hand inventory. These triggers are static and are not dynamically adjusted when disruptions occur. Perhaps, further research could explore the impact of dynamic expediting triggers.

Our findings leave no doubt that variability in quantity and timing, whether from normal operations, disruptions, or expediting, tends to be amplified in supply chains. It is important to recognize that model extensions, such as those we suggest for future work, would likely further increase this variability and amplification. This recognition leads to the conclusion that problem tractability constitutes a key challenge for treating real-world supply chains, and that improved metaheuristics for solving global optimization problems is critical for future advances. The practical value of our contribution is affirmed by the N-ABLE Project Leader from Sandia National Laboratories: “[This work] demonstrated the importance of careful design in modeling the realities of supply chain behavior, and provided strong motivation for further simulation development and experimentation.”

Appendix A: Experimental design specifications

This appendix covers modeling details and justifications in our application of inventory policy, forecasting, buffering, order sizes, lead times, and statistical analysis.

A.1. Forecasting and buffering

We apply an autoregressive process AR(1) to model customer demand at Echelon 1. The customer demand as observed in period t at Echelon 1 is of the form: $D_t = \mu + \rho D_{t-1} + \varepsilon_t$, with $\mu = 100$, $\rho = .1$, and independent and identically distributed random variables ε_t with distribution $N(0, \sigma = 15)$. In this process, the expected demand is $\mu/(1-\rho) = 111$.

Companies frequently experience auto-correlated demand [46]. Demand functions such as ours have been used in many studies, including Lee et al. [42], and Chen et al. [72]. Our interviews revealed that operating managers within the case firms and their suppliers seldom share point-of-sale data. Most were familiar with features of the Beer Game, and claimed that their processes encountered the full effects of demand amplification. There was strong consensus that the way to model reality across firms is through local forecasting and buffering. They also rescheduled frequently (expediting some orders, and postponing others) without the benefit of shared data across firms. We recognize however, the existence of progressive supply chains that plan more holistically [88].

Most products consist of many components. We considered assembly of two components. With local planning, a convenient way to address service level requirements for assembly systems is to increase the z value of each of the components to reflect the joint probabilities of having more components in assembly.

Parameters in demand generation and inventory control play important roles in controlling bullwhip effects [89]. Order variability induces demand amplification, even when the only source of uncertainty is with final customer demand [42,44]. We chose to keep the system in control by collectively searching α (smoothing parameter) and z (service level parameter) values in pilot experiments as a means to achieve a reasonable service level at Echelon 1, as benchmarked in our cases. At any period, α is the weight for the current demand data, while $(1-\alpha)$ is the weight on the forecast for the last period. As such, α and its complement govern the weighting of demands in each prior period forecast. A relatively small α discounts the effect of changes in the current demand, relative to prior demands reflected in the forecast from the last period. Therefore, small α may limit the amplification of order variability progressing across the echelons of a supply chain. The service level parameter z is used to calculate safety stock for a particular echelon. Safety stock serves to maintain a prescribed service level for that echelon.

We focused the pilots on base case conditions (no expediting or disruption). Across echelons, we tried three z values {2, 2.5, 3} and α values in increments of .05 over the range [.01, .51]. A value of $z=2$ under i.i.d demand theoretically ensures a 95% service level at a single echelon [55]. Yet with $z=2$ at each stage in our system, no values of α could achieve a service level of 95% at the final echelon. Chen et al. [44,72] found in a less complex system that demand amplification increases with higher values of z and α. We observed similar behavior in the pilots. With $z=2.5$, α values below .01 were needed at all stages to attain a service level of at least 95%. Consequently in subsequent experimentation, the z values were held fixed at our highest experimental levels (3.0) at all echelons and stages to allow practical α values [24]. We achieved a service level of 95% at Echelon 1 with α values of .21, .11, .06, and .01, respectively, for Echelons 1 through 4. We applied these parameters in subsequent experiments.

A.2. Lot sizes

We restrict order sizes to cover accumulated requirements between review periods. In practice, batching can be applied at every echelon as well to address order, setup, and minimum-shipment elements, but we dispense with these issues in the experiments. We are interested in exploring a minimum set of conditions (stationary demand, no order cost, no setup cost, no setup time, no returns, an infinite production rate, and static lead times) to support future research on the Key Issues under more robust operating conditions.

A.3. Lead times

Lead time logic and parameters are noteworthy. When expediting is activated, we experimented in pilots with a range of parameters for each order trigger to achieve expediting of about 10–15% of the orders, a frequency observed in the case applications. We embedded two types of triggers to expedite production and transportation times. One corresponds to lead time demand. The other occurs when on-hand inventory falls below a demand-based target [35]. We found reasonable parameters for this second trigger of average demand at Echelon 1, two times average

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demand at Echelon 2, three times at Echelon 3, and four times at Echelon 4.

Our use of point estimates for lead times enables us to examine behavior in a relatively complicated supply system, where variability is introduced solely through disruptions, expediting, and Echelon 1 demand. We considered the cases and literature in the selection of regular, expedited, and disrupted times. Our lead times depicted in Fig. 1 fall roughly midway between ranges observed in our cases. However, we found little guidance in the literature on disruptions for lead time choices, expediting, and bullwhip effects. Many of these models assume fixed or no regular lead times without rationale. We noted substantial differences across studies in the times used for regular, disrupted, and expedited states, as well as for demand during the various lead times, and the lead-time demands of normal relative to disrupted and expedited states. The parameters in our experiments fell well within these wide ranges.

A.4. Statistical issues

We draw from the experimental designs of literature on bullwhip effects most closely related to our problem context [48–51]. It was important in the simulation experiments that our initiation period was long enough to remove transient effects. We chose a run length sufficient to facilitate the interesting statistical results that we have observed. Each simulation was run for 2000 days. The first 1000 established steady state conditions. Performance was observed over the remaining time. We found that across 100 pilot replications, a fifty-period moving average of order-up-to quantities showed convergence after about 600 periods at all echelons and stages. See Welch's warm-up procedure in Law and Kelton [90], Chapter 9. A fifty period base was long enough for our model to enable a few order placements.

Finally, we distinguish issues of independence of a performance measure within and across replications. We do not claim or expect independence within replications either in demand or supply. Demand is by definition autocorrelated over time, and inventory levels and replenishment orders are clearly linked from one period to the next. Indeed, we wish to allow bullwhip effects over time to reflect practical behavior within each replication.

Across replications, however, we desired independence. We attempted to induce independence by applying terminating sampling. We chose independent random number seeds to initiate replications in half the samples, and in the other half, antithetic random numbers were used to increase statistical rigor [90]. We followed by testing for latent dependencies among the three simulated performance metrics using MANOVA. This tool is capable of detecting correlations among dependent variables and offering overall statistical tests across them. In our experiments, the various MANOVA tests indicated that values from each of the three process metrics (dependent variables) are drawn from separate distributions, according to four different statistical tests (Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root). This enabled us to analyze the dependent variables separately (essentially as ANOVA experiments), but we took care to draw conclusions only in dominant cases where the results across dependent variables supported one another.

References

[1] Boudway I. What catastrophe costs. Bloomberg Businessweek; December 22, 2011–January 8, 2012, 82.
[2] Cooper S, Hedde C, Rauch E, Hartwig R. NAT CATS 2014: Whats going on with the weather? Munich RE [07.01.15].
[3] Beverly R, Rodysill J. Risky business. Outlook Journal, http://www.accenture.com/Global/Research_and_Insights/Outlook/By_Issue/Y2007/RiskyBusiness.htm; 2007 [accessed 14.08.07].
[4] Hendricks KB, Singhal VR. The effect of supply chain glitches on shareholder value. Journal of Operations Management 2003;21(5):501–22.
[5] Hendricks KB, Singhal VR. Association between supply chain glitches and operating performance. Management Science 2005;51(5):695–711.
[6] Hendricks KB, Singhal VR. An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. Production and Operations Management 2005;14(1):35–52.
[7] Kumar S, Liu J, Scutella J. Stockholder wealth and supply chain disruptions in Indian companies. International Journal of Physical Distribution and Logistics Management 2015;45(9–10):938–58.
[8] Filbeck G, Kumar S, Zhao X. Competitor stock price reaction to supply chain disruptions. Journal of Business Economics and Perspectives 2014:24–66.
[9] Mitroff II, Alpaslan MC. Preparing for evil. Harvard Business Review 2003;81:109–15.
[10] Craighead CW, Blackhurst J, Rungtusanatham JM, Handfield RB. The severity of supply chain disruptions: design characteristics and mitigation capabilities. Decision Science 2007;38(1):131–56.
[11] Heckmann I, Comes T, Nickel A. A critical review on supply chain risk – definition, measure and modeling. Omega 2015;52:119–32.
[12] Snyder LV, Shen ZJM. Supply and demand uncertainty in multi-echelon supply chains. Working Paper. Lehigh University; 2009.
[13] Berk E, Arreola-Risa A. Note on future supply uncertainty in EOQ models. Naval Research Logistics 1994;41(1):129–32.
[14] Parlar M, Perry D. Analysis of a (Q; r; T) inventory policy with deterministic and random yields when future supply is uncertain. European Journal of Operations Research 1995;84(2):431–43.
[15] Arreola-Risa A, DeCroix GA. Inventory management under random supply disruptions and partial backorders. Naval Research Logistics 1998;45(7):687–703.
[16] Snyder LV, Atan Z, Peng P, Rong Y, Schmitt AJ, Sinsoysal B. OR/MS models for supply chain disruptions: a review. IIE Transactions 2016;48(2):89–109.
[17] Lewis BM, Erera AL, Nowak CC, White CC. Managing inventory in global supply chains facing port-of-entry disruption risks. Transport Science 2013;47(2):162–80.
[18] Tomlin BT, Snyder LV. On the value of a threat advisory system for managing supply chain disruptions. Working Paper. University of North Carolina at Chapel Hill; 2009.
[19] Tomlin BT. On the value of mitigation and contingency strategies for managing supply chain disruption risks. Management Science 2006;52(5):639–57.
[20] Tomlin BT, Wang Y. On the value of mix flexibility and dual sourcing in unreliable newsvendor networks. Manufacturing & Service Operations Management 2005;7(1):37–57.
[21] Qi L, Shen ZM, Snyder LV. The effect of supply disruptions on supply chain design decisions. Transport Science 2010;44(2):274–89.
[22] Wu OQ, Chen H. Optimal control and equilibrium behavior of production-inventory systems. Management Science 2010;56(8):1362–79.
[23] Schmitt AJ, Sun SA, Snyder LV, Shen ZJM. Centralization versus decentralization: risk pooling, risk diversification, and supply uncertainty in a one-warehouse multiple-retailer system. Omega 2014;52(April):201–12.
[24] Snyder RD, Koehler AB, Hyndman RJ, Ord JK. Exponential smoothing models: means and variances for lead-time demand. European Journal of Operations Research 2004;158(2):444–55.
[25] Chopra S, Sodhi MS. Managing risk to avoid supply chain breakdown. Sloan Management Review 2004;46(1):61–3.
[26] Svensson G. A conceptual framework for the analysis of vulnerability in supply chains. International Journal of Physical Distribution and Logistics Management 2000;30(9):731–49.
[27] Sheffi Y, Rice J. A supply chain view of the resilient enterprise. MIT Sloan Management Review 2005;47(1):41–8.
[28] Zsidisin GA, Ragatz GL, Melnyk SA. Supply continuity planning: taking control of risk. Supply Management 2005;16(1):21–6.
[29] Kleindorfer P, Saad G. Managing disruption risks in supply chains. Production and Operations Management 2005;14(1):53–68.
[30] Knemeyer AM, Zinn W, Eroglu C. Proactive planning for catastrophic events in supply chains. Journal of Operations Management 2009;27(2):141–53.
[31] Stecke KE, Kumar S. Sources of supply chain disruptions, factors that breed vulnerability, and mitigating strategies. Journal of Marketing Channels 2009;16(3):193–226.
[32] Sheffi Y. The resilient enterprise: overcoming vulnerability for competitive advantage. Cambridge (MA): MIT Press; 2007.
[33] Klibi W, Martel A. Scenario-based supply chain network risk modeling. European Journal of Operations Research 2012;223:644–58.
[34] Schmitt AJ, Singh M. A quantitative analysis of disruption risk in a multi-echelon supply chain. International Journal of Production Economics 2012;22:32.
[35] Beyer D, Ward. J. Network server supply chain at HP: a case study. [Chapter 8]. In: Song J, Yao D, editors. Supply chain structures: coordination, information and optimization. Norwell (MA): Kluwer Academic Publishers; 2002.
[36] Kelleher K. Why FedEx is gaining ground. Business 2.0, 56–57 October 2003.
[37] Souder E. Retailers rely more on fast deliveries. Wall Street Journal 2004.
[38] Robinson LW, Bradley JR, Thomas LJ. Consequences of order crossover under order-up-to inventory policies. Manufacturing & Service Operations Management 2001;3(3):175–88.
[39] Kim T, Glock CH, Kwon, Y. A closed-loop supply chain for deteriorating products under stochastic container return times. Omega 2014;43(March):30–40.

[40] Veeraraghavan S, Scheller-Wolf A. Now or later: a simple policy for effective dual sourcing in capacitated systems. Operations Research 2008;56(4):850–64.
[41] Levy DL. International sourcing and supply chain stability. Journal of International Business Studies 1985;26(2):343–60.
[42] Lee HL, Padmanabhan V, Whang S. Information distortion in a supply chain: the bullwhip effect. Management Science 1997;43(4):546–58.
[43] Disney SM, Towill DR. On the bullwhip and inventory variance produced by an ordering policy. Omega 2003;31(3):157–67.
[44] Chen F, Drezner Z, Ryan JK, Simchi-Levi D. Quantifying the bullwhip effect in a simple supply chain: the impact of forecasting, lead times and information. Management Science 2000;46(3):269–86.
[45] Chen L, Lee HL. Information sharing and order variability control under a generalized demand model. Management Science 2009;55(5):781–97.
[46] Lee HL, So KC, Tang CS. The value of information sharing in a two-level supply chain. Management Science 2000;46(5):626–43.
[47] Sodhi MS. Managing demand risk in tactical supply chain planning for a global consumer electronics company. Production and Operations Management 2005;14(1):69–79.
[48] Fiala P. Information sharing in supply chains Omega 2005; 3(5):419–23.
[49] Chatfield D, Kim J, Harrison T, Hayya J. The bullwhip effect – impact of stochastic lead times, information quality, and information sharing: a simulation study. Production and Operations Management 2004;13(4):340–53.
[50] Sterman J. Modeling managerial behavior: misperceptions of feedback in a dynamic decision making experiment. Management Science 1989;35(3):321–39.
[51] Croson R, Donohue K. Behavioral causes of the bullwhip effect and the observed value of inventory information. Management Science 2006;52 (3):323–36.
[52] Sarkar S, Kumar S. A behavioral experiment on inventory management with supply chain disruption. International Journal of Production Economics 2015;169:169–78.
[53] Rong Y, Snyder LV, Shen ZM. Bullwhip and reverse bullwhip effects under the rationing game. Working paper, Lehigh University; 2009. Available at 〈http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1240173〉.
[54] Rong Y, Shen ZM, Snyder LV. The impact of ordering behavior on order-quantity variability: a study of forward and reverse bullwhip effects. Flexible Server Manufacturing Journal 2009;20(1):95–124.
[55] Nahmias S. Production and operations analysis (8th ed.). Burr Ridge, IL: Irwin; 2008.
[56] Axsater S. Inventory control. 2nd ed.. Norwell (MA): Kluwer Academic Publishers; 2006.
[57] Huh WT, Janakiraman G, Muckstadt JA, Rusmevichientong P. Asymptotic optimality of order-up-to policies in lost sales inventory systems. Management Science 2009;55(3):404–20.
[58] Ross AM, Rong Y, Snyder LV. Supply disruptions with time-dependent parameters. Computer Operations Research 2008;35(11):3504–29.
[59] Benjaafar S, ElHafsi M, Lee C, Zhao W. Optimal control of an assembly system with multiple stages and multiple demand classes. Operations Research 2011;59(2):522–9.
[60] Eidson ED, Ehlen MA. NISAC Agent-Based laboratory for economics (N-ABLE): overview of agent and simulation architectures. SAND2005-0263. Albuquerque (NM): Sandia National Laboratories; 2005.
[61] Downes PS, Ehlen MA, Mackey GE. Multi-modal transportation and commodity flow modeling in N-ABLE™. SAND2006-6586. National Infrastructure Simulation & Analysis Center; 2006.
[62] Ehlen MA, Downes PS, Scholand AJ. A mesoeconomic model of the regional impacts of natural and man-made disruptive events. SAND2009-0206. Albuquerque (NM): Sandia National Laboratories; 2008.
[63] Ehlen MA, Downes PS, Scholand AJ. A Post-Katrina comparative economic analysis of the chemicals, food, and Goodyear value chains (OUO). U.S. Department of Homeland Security, National Infrastructure Simulation & Analysis Center; 2007.
[64] Blome C, Schoenherr T. Supply chain risk management in financial crisis – a multiple case-study approach. International Journal of Production Economics 2011;134(1):43–57.
[65] Juneja M, Rajamani D. Lecture series: consumer electronics supply chain management. Available at 〈https://som.utdallas.edu/c4isn〉; 2013 [accessed December 2013].
[66] Swaminathan JM, Smith SF, Sadeh NM. Modeling supply chain dynamics: a multiagent approach. Decision Science 1998;29(3):607–32.
[67] Schonberger RJ. Best practices in lean six sigma process improvement. [Chapter 6]. John Wiley & Sons; 2008. p. 56–70.
[68] Schonberger RJ. Lean performance management (metrics don't add up). Cost Management 2008:5–10.
[69] Schmitt AJ. Strategies for customer service level protection under multi-echelon supply chain disruption risk. Transport Research Part B: Methodology 2011;45(8):1266–83.
[70] Haisheng Y, Zeng AG, Zhao L. Single or dual sourcing: decision-making in the presence of supply chain disruption risks. Omega 2009;37(4):788–800.
[71] Arbuckle JL. Amos 6.0 User's Guide. Chicago, IL: SPSS Inc.; 2005.
[72] Chen YF, Ryan JK, Simchi-Levi D. The impact of exponential smoothing forecasts on the bullwhip effect. Naval Research Logistics 2000;47(4):271–86.
[73] Bradley JR. Managing assets and subcontracting policies [Ph.D. dissertation]. Stanford, CA: Stanford University; 1997.
[74] Groenevelt H, Rudi N. A base stock inventory model with possibility of rushing part of order. Working Paper. Rochester (NY): Simon School of Business, University of Rochester; 2003. 〈https://www.kellogg.northwestern.edu/meds/papers/Sz.pdf〉.
[75] Schmitt T. Resolving uncertainty in manufacturing systems. Journal of Operations Management 1984;4(4):331–45.
[76] Cohen M, Ho T, Ren J, Terwiesch C. Measuring imputed cost in the semiconductor equipment supply chain. Management Science 2003;49(12):1653–70.
[77] Arslan H, Ayhan H, Olsen TL. Analytic models for when and how to expedite in make-to-order systems. IIE Transactions 2001;33(11):1019–30.
[78] Goldberg DE. Genetic algorithms in search, optimization, and machine learning. Reading (MA): Addison-Wesley; 1989.
[79] Faaland BH, Schmitt TG, Arreola-Risa A. Economic lot scheduling with lost sales and setup times. IIE Transactions 2004;36(7):629–40.
[80] Boer G, Jeter D. What's new about modern manufacturing? Empirical evidence on manufacturing cost changes Journal of Management Account Research 1993;5:61–83.
[81] Janakiraman G, Roundy RO. Lost-sales problems with stochastic lead times: convexity results for base-stock policies. Operations Research 2004;52 (5):795–803.
[82] Ugray Z, Lasdon L, Plummer J, Glover F, Kelly J, Marti R. A multistart scatter search heuristic for smooth NLP and MINLP problems. In: Rego C, Alidaee B, editors. Metaheuristic optimization via memory and evolution. Kluwer Academic Publishers; 2005. p. 25–58.
[83] Ugray Z, Lasdon L, Plummer J, Glover F, Kelly J, Marti R. Scatter search and local NLP solvers: a multistart framework for global optimization. INFORMS Journal of Computation 2007;19(3):328–40.
[84] Duarte A, Marti R, Gortazar F, Glover F. Hybrid scatter Tabu Search for unconstrained global optimization. Annals of Operations Research 2009;183 (1):95–123.
[85] Hvattum LM, Glover F. Finding local optima of high-dimensional functions using direct search methods. European Journal of Operational Research 2009;195:31–45.
[86] Better M, Glover F, Laguna M. Advances in analytics: integrating dynamic data mining with simulation optimization. IBM Journal of Research Development 2007;51(3–4):477–87.
[87] Janakiraman G, Seshadri S, Shanthikumar G. A comparison of the optimal costs of two canonical inventory systems. Operations Research 2007;55(5):866–75.
[88] Brown KA, Schmitt TG, Schonberger RJ, Dennis S. QUADRANT homes applies lean/JIT concepts in a project environment. Interfaces 2004;34(6):442–50.
[89] Baganha MP, Cohen MA. The stabilizing effect of inventory in supply chains. Operations Research 1998;46(3):572–83.
[90] Law AM, Kelton WD. Simulation modeling and analysis. New York (NY): McGraw-Hill; 2000.