

Simple Heuristics for Optimal Inventory Policies in Supply Chains

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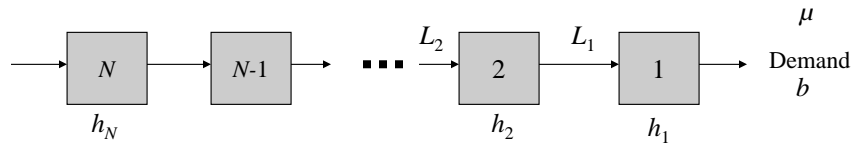


Motivations for Simple Heuristics



- The form of the optimal policy for most supply chains is unknown
- Hard to solve - exact optimization algorithms involve recursive calculations between stages across time
- Little intuition from the algorithm
- Hard to communicate
- Hard to coordinate the supply chain
- Difficult to solve joint problems (inventory/pricing, inventory/cash flows, etc.)

The Basic Model



- i.i.d demand between periods with mean μ
- The objective is to minimize the average total cost per period
- Centralized vs. local information
- Continuous review vs. periodic review

Systems and Inventory Policies



- Continuous-review system
 - Poisson demand
 - Echelon (r, Q) policies
 - Assuming a fixed cost k_j for Q_j
 - Satisfying integer-ratio constraints: $Q_j = n_j Q_{j-1}$
- Periodic-review system
 - i.i.d demand between periods
 - Echelon (s, T) policies
 - Assuming a fixed cost K_j for T_j
 - Satisfying integer-ratio constraints: $T_j = n_j T_{j-1}$

Single-stage Systems



- (r, Q) policies

$$C(r, Q) = \frac{k\lambda + \sum_{x=1}^Q G(r+x)}{Q}$$

where $G(y) = E[h(y - D(L))^+ + b(y - D(L))^-]$

- (s, T) policies

$$C(s, T) = \frac{K}{T} + G(s, T)$$

where

$$G(y, T) = \frac{1}{T} \left(\sum_{\tau=0}^{T-1} E[h(y - D[L + \tau])^+ + b(y - D[L + \tau])^-] \right)$$

CONTINUOUS-REVIEW SYSTEM



Echelon (r, Q) Policies



- Cost evaluation for any given (r, Q) policies:

$$G_1(y) = E[h_1(y - D[L_1]) + (b + h_{[1, N]})(y - D[L_1])^-]$$

For $j = 2, \dots, N$,

$$G_j(y) = E[h_j(y - D[L_j]) + G_{j-1}(O_{j-1}[y - D[L_j]])]$$

where $O_j[x] = \begin{cases} x, & \text{if } x \leq r_j, \\ x - mQ_j, & \text{otherwise} \end{cases}$

$$C(r, Q) = \sum_{i=1}^N (k_i \lambda) / Q_i + \sum_{x=1}^{Q_N} G_N(r_N + x) / Q_N$$

- Optimal reorder point r_j^* can be found recursively from stage 1, 2, ..., until stage N

$$r_1^* = \arg \min_y \bar{G}_1(y) \triangleq \sum_{x=1}^{Q_1} G_1(y + x)$$

$$r_j^* = \arg \min_y \bar{G}_j(y) \triangleq \sum_{x=1}^{Q_j} G_j(y + x)$$

Heuristic for optimal reorder points



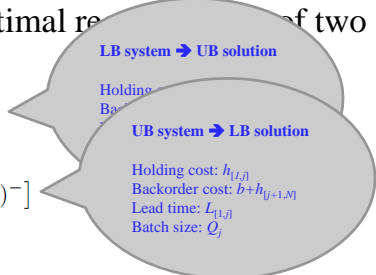
- For fixed Q , r_j^* is bounded by the optimal reorder points of two single-stage systems

$$G_j^{\ell}(y) = E[h_j(y - \tilde{D}_j)^+ + (b + h_{[j+1, N]})(y - \tilde{D}_j)^-]$$

$$G_j^u(y) = E[h_{[1, j]}(y - \tilde{D}_j)^+ + (b + h_{[j+1, N]})(y - \tilde{D}_j)^-]$$

$$r_j^u = \arg \min_y \left(\sum_{x=1}^{Q_j} G_j^{\ell}(y + x) \right)$$

$$r_j^{\ell} = \arg \min_y \left(\sum_{x=1}^{Q_j} G_j^u(y + x) \right)$$



Theorem 1 (Shang and Song [34]). For $j = 1, \dots, N$, (1) $G_j^u(y) + \tau_j \geq G_j(y) \geq G_j^{\ell}(y) + \tau_j$ for all y , and (2) $r_j^{\ell} \leq r_j^* \leq r_j^u$. When $j = 1$, the above inequalities reduce to equalities.

Heuristics for Optimal Batch Sizes



- We propose two heuristics for finding the optimal batch sizes
- These two heuristics are inspired by solving the following problem:

$$\min \sum_{j=1}^N C_j^{\ell}(Q_j)$$

$$\text{s.t. } Q_j \geq Q_{j-1}, \quad j = 2, \dots, N$$

$$\text{where } C_j^{\ell}(Q_j) = \frac{k_j \lambda}{Q_j} + \frac{1}{Q_j} \sum_{x=1}^{Q_j} G_j^{\ell}(r_j(Q_j) + x)$$

$$\text{and } r_j(Q_j) = \arg \min_y \sum_{x=1}^{Q_j} G_j^{\ell}(y + x),$$

$$G_j^{\ell}(y) = \mathbb{E}[h_j(y - \tilde{D}_j)^+ + (b + h_{[j+1, N]})(y - \tilde{D}_j)^-]$$

- A clustering algorithm generates a solution

Simplifying the Computation



The solution obtained from the cluster algorithm is close to the solution obtained from the following two-step procedure (Shang 2008)

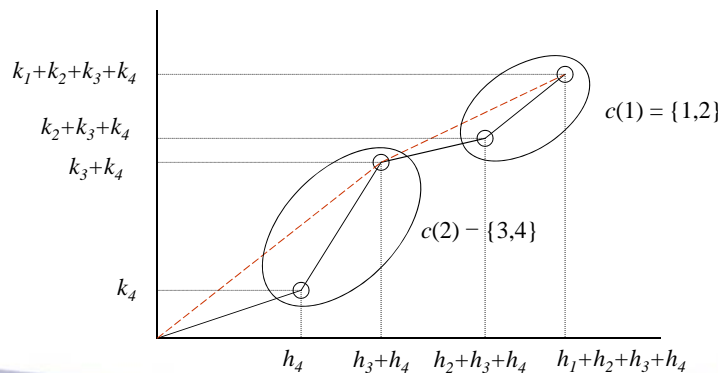
- Clustering
- Minimization

Clustering



Let $\{c(1), c(2), \dots, c(M)\}$ be the clusters

For the cluster $c(m)$, assume there are $n(m)$ stages, $m=1, \dots, M$



Minimization



Let $Q_{c(m)}$ is the batch size for the stages in $c(m)$, and define

$$h[m] = \sum_{i \in c(m)} h_i, \quad h'[m] = \sum_{i \in c(m)} h_{[i, N]}, \quad \text{and} \quad k[m] = \sum_{i \in c(m)} k_i.$$

Heuristic 1. $Q_{c(m)}$ is the solution of the following problem:

$$\min_Q \left\{ \frac{\lambda \cdot k[m] + \sum_{x=1}^Q G_{c(m)}^\ell(R^\ell(Q) + x)}{Q} \right\},$$

s.t. $Q = qQ_{c(m-1)}, \quad q \in \mathfrak{S}^+, \quad m > 1,$

where

$$R^\ell(Q) = \arg \min_y \left\{ \sum_{x=1}^Q G_{c(m)}^\ell(y + x) \right\}, \quad G_{c(m)}^\ell(y) = \sum_{i \in c(m)} G_i^\ell(y),$$

and

$$G_i^\ell(y) = \mathbb{E}[h_i(y - \tilde{D}_i) + (b + h_{[i, N]})(y - \tilde{D}_i)^-].$$

Minimization



Heuristic 2. Suppose that $c(m)$ contains stage $i \in \{v, v+1, \dots, v+n(m)-1\}$.

$Q_{c(m)}$ is the solution of the following problem:

$$\min_Q \left\{ \frac{\lambda k[m] + \sum_{x=1}^Q G_{c(m)}(R(Q) + x)}{Q} \right\},$$

$$\text{s.t. } Q = qQ_{c(m-1)}, \quad q \in \mathfrak{S}^+, \quad m > 1,$$

where

$$R(Q) = \arg \min_y \left\{ \sum_{x=1}^Q G_{c(m)}(y + x) \right\},$$

and

$$G_{c(m)}(y) = E[h[m](y - \tilde{D}_{v+n(m)-1}) + (n(m)b + h'[m])(y - \tilde{D}_{v+n(m)-1})^-].$$

Effectiveness of the Heuristics



Table 1. Performance summary for Variant 1, Variant 2, and the EOQ heuristic in Group 1.

	Variant 1		Variant 2		The EOQ heuristic	
	$b = 10$	$b = 50$	$b = 10$	$b = 50$	$b = 10$	$b = 50$
0%	193	309	137	307	31	5
(0.0%, 0.5%]	262	157	316	153	378	350
(0.5%, 1.0%]	25	26	24	30	57	128
(1.0%, 1.5%]	12	8	11	10	6	15
(1.5%, 2.0%]	4	4	6	4	6	6
(2.0%, 2.5%]	8	0	10	0	20	0
(2.5%, 3.0%]	0	1	0	1	6	4
3.0% above	8	7	8	7	8	4
Average (%)	0.21	0.13	0.24	0.14	0.41	0.40



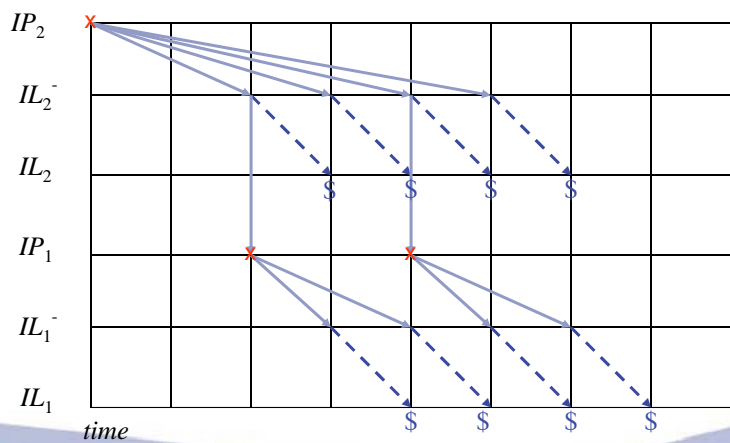
PERIODIC-REVIEW SYSTEM



Echelon (s, T) Policies: Inventory Dynamics



- Two-stage system, $T_2=4, T_1=2, L_2=2, L_1=1$



Optimizing Base-stock Levels with Fixed T: Chao and Zhou (2009)



- Focus on a regenerative cycle. Characterize IP_j, IL_j for stage $j = N, N-1, \dots, 1$
- A bottom-up recursion: Define $\mathbf{T}_j = (T_1, T_2, \dots, T_j)$

$$G_1(y, \mathbf{T}_1) = \frac{1}{T_1} \left(\sum_{\tau=0}^{T_1-1} E[h_1(y - D[L_1 + \tau]) + (b + h_{1,N})(y - D[L_1 + \tau])^-] \right)$$

$$s_1(\mathbf{T}_1) = \operatorname{argmin}_y G_1(y, \mathbf{T}_1)$$

For $j = 2, \dots, N$,

$$G_j(y, \mathbf{T}_j) = \frac{1}{T_j} \sum_{\tau=0}^{T_j-1} E \left[h_j(y - D[L_j + \tau]) + G_{j-1} \left(\min \left\{ y - D \left[L_j + \left\lfloor \frac{\tau}{T_{j-1}} \right\rfloor T_{j-1} \right\}, s_{j-1}(\mathbf{T}_{j-1}) \right\}, \mathbf{T}_{j-1} \right) \right]$$

$$s_j(\mathbf{T}_j) = \operatorname{argmin}_y G_j(y, \mathbf{T}_j)$$

$$C(\mathbf{T}) = \sum_{j=1}^N \left(\frac{K_j}{T_j} \right) + G_N(s_N(\mathbf{T}_N), \mathbf{T}_N) \quad (\text{Average total cost per period})$$

For simplicity, let $s_j^* = s_j(\mathbf{T}_j)$



Heuristic for Optimal Base-stock Levels



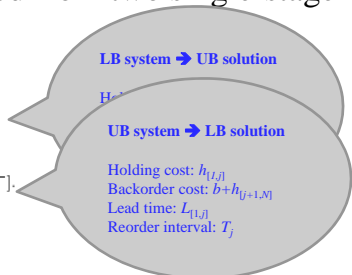
- s_j^* is bounded by the solutions obtained from two single-stage systems with (s, T) policies

$$G_j^L(y) = \frac{1}{T_j} \sum_{\tau=0}^{T_j-1} E[h_j(y - D[L_{1,j} + \tau]) + (b + h_{j,N})(y - D[L_{1,j} + \tau])^-],$$

$$G_j^U(y) = \frac{1}{T_j} \sum_{\tau=0}^{T_j-1} E[h_{1,j}(y - D[L_{1,j} + \tau]) + (b + h_{1,N})(y - D[L_{1,j} + \tau])^-].$$

Let

$$s_j^L = \operatorname{argmin}_y G_j^L(y), \quad s_j^U = \operatorname{argmin}_y G_j^U(y).$$



Proposition 3 (Shang and Zhou [35]). For $j = 1, \dots, N$,

- (1) $G_j^L(y) + \pi_j \leq G_j(y) \leq G_j^U(y) + \pi_j$;
- (2) $s_j^L \leq s_j^* \leq s_j^U$.



Heuristic for Optimal Reorder Intervals



$$\text{Min}_{\mathbf{T}} \sum_{j=1}^N \left(\frac{K_j}{T_j} \right) + G_N(\mathbf{T}_N)$$

subject to
 $T_{j+1} = n_j T_j,$
 $T_j, n_j \in \text{positive integer},$
 $j = 1, \dots, N-1$

Decomposition

$$\text{Min}_{\mathbf{T}} \sum_{j=1}^N \left(\frac{K_j}{T_j} + g_j(\mathbf{T}_j) \right)$$

subject to
 $T_{j+1} = n_j T_j,$
 $T_j, n_j \in \text{positive integer},$
 $j = 1, \dots, N-1$

Lower bound

Upper bound

$$\text{Min}_{\mathbf{T}} \sum_{j=1}^N \left(\frac{K_j}{T_j} + \underline{g}_j(\mathbf{T}_j) \right)$$

subject to
 $T_{j+1} \geq T_j,$
 $j = 1, \dots, N-1$

$$\text{Min}_{\mathbf{T}} \sum_{j=1}^N \left(\frac{K_j}{T_j} + \bar{g}_j(\mathbf{T}_j) \right)$$

subject to
 $T_{j+1} \geq T_j,$
 $j = 1, \dots, N-1$

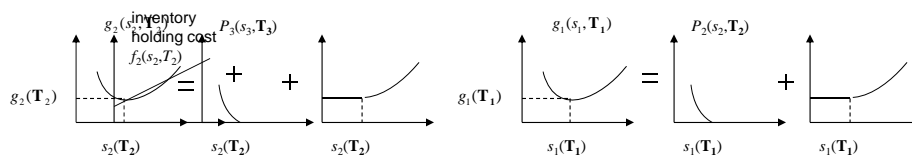
Decomposition of the Total Cost Function



Use the "induced-penalty cost function" P_j to decouple the system cost

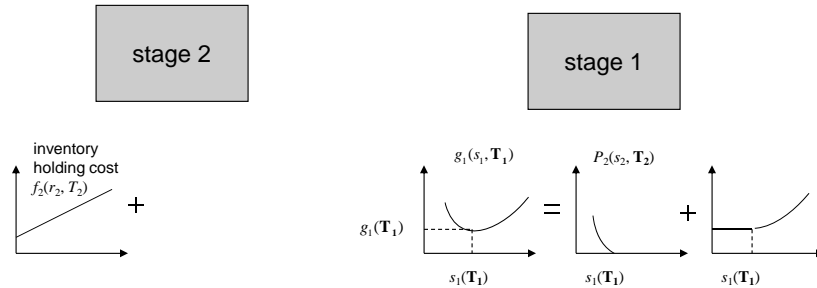
stage 2

stage 1

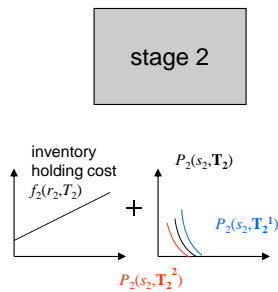


$$G_j(\mathbf{T}_j) = \sum_{i=1}^j g_i(\mathbf{T}_i), \quad j = 1, \dots, N$$

Bounds on the Stage Cost



Bounds on the Stage Cost



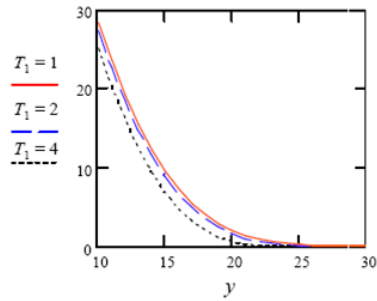
Define

$$T_j^j = (T_j, T_j, \dots, T_j) \text{ and } T_j^1 = (1, 1, \dots, 1, T_j)$$

When stage j 's downstream stages use the same reorder interval as T_j (one), the resulting P_j is a lower (an upper) bound to the original P_j , i.e.,

$$P_j(y, T_j^j) \leq P_j(y, T_j) \leq P_j(y, T_j^1)$$

Bounds on the Induced-Penalty Cost Function: An Example



A two-stage example with $h_1 = h_2 = 0.5$,
 $L_1 = L_2 = 1$, $b = 9$.

Heuristic I



Let $\bar{g}_j(T_j) = g_j(T_j^1)$

(UP)
$$\text{Min}_T \sum_{j=1}^N \left(\frac{K_j}{T_j} + \bar{g}_j(T_j) \right)$$

subject to

$$T_{j+1} \geq T_j, \quad j = 1, \dots, N-1$$

- Solve both (UP) and (LP) problems
- Clustering algorithm
- The heuristic solution is whichever yields the smaller cost

Let $\underline{g}_j(T_j) = g_j(T_j^2)$

(LP)
$$\text{Min}_T \sum_{j=1}^N \left(\frac{K_j}{T_j} + \underline{g}_j(T_j) \right)$$

subject to

$$T_{j+1} \geq T_j, \quad j = 1, \dots, N-1$$

- The above decomposition leads to an algorithm to find the optimal reorder intervals; see Shang and Zhou (2010)

Heuristic II



- Approximate the stage cost function $g_j(\mathbf{T}_j)$ by the lower-bound cost function

$$g_j^h(s_j, T_j) = \frac{1}{T_j} \sum_{\tau=0}^{T_j-1} \mathbb{E}[h_j(s_j - D[L_{[1,j]} + \tau]) + (b + h_{[j,N]})(y - D[L_{[1,j]} + \tau])^-]$$

$$\text{Let } g_j^h(\tilde{T}_j) = g_j^h(s_j(T_j), T_j), \text{ and } C_j^h(T_j) = K_j/T_j + g_j^h(T_j)$$

- Solve

$$\min_{\mathbf{T}} \sum_{j=1}^N C_j^h(T_j)$$

$$\text{s.t. } T_{j+1} = n_j T_j, \quad j = 1, \dots, N-1.$$

- The two-step optimization procedure introduced in the (r, Q) policy would likely work well



NON-STATIONARY DEMAND



Non-stationary Demand Model



- Non-stationary demand is prevalent
 - Product life cycles
 - Seasonality
 - Business cycles
 - Trends
- Non-stationary demand complicates inventory decisions
 - Computation
 - Implementation
- Propose a simple solution to resolve the above issues



The C-S model with non-stationary demand



- Clark and Scarf (1960) show that (time-varying) echelon base-stock policies are optimal
- Let $s_j(t)$ be optimal echelon base-stock level, $j = 1, \dots, N$
 - Stage j reviews x_j and orders up to $s_j(t)$ if $x_j < s_j(t)$; does not order otherwise
- $s_j(t)$ can be obtained by solving j sets of dynamic programs recursively:
 - Find $s_1(t)$ by solving a DP formulated from a single-stage system
 - With known $s_1(t)$, generate an induced-penalty cost function
 - Charge the penalty cost to stage 2, and formulate a DP to find $s_2(t)$
 - Repeat the procedure recursively
- In short, the optimal value function of an upstream stage depends on all of its downstream stages' optimal base-stock levels



Main results



- Construct an upper bound and a lower bound for $s_j(t)$ in each period t
 - By solving single-stage, finite-horizon problems with original parameters
- Propose a simple heuristic by solving N single-stage problems
 - Reduce the computation time and complexity
- Provide an analytical approximation for optimal base-stock levels and safety stocks
 - Reveal analytical insights on managing inventory
- Propose a simple, time-consistent contract that (nearly) coordinates the supply chain in the finite horizon
 - Facilitate the implementation of the centralized solution



Idea of constructing solution bounds



For each echelon $j, j=1, \dots, N$

- Construct an upper-bound system by restricting stage i to always order up to the echelon inventory level x_{i+1} , for $i < j$
 - Is the resulting solution from the upper-bound system a lower bound to $s_j(t)$ in each period?
- Construct a lower-bound system by setting $h_i=0, c_i=0$, for $i < j$
 - Is the resulting solution from the lower-bound system an upper bound to $s_j(t)$ in each period?
- Are the lower and upper bound systems equivalent to a single-stage system? If so, what are the resulting parameters?



Upper-bound system



The lower-bound solution $s_j^\ell(t)$ can be found by solving the upper-bound system, denoted by $S_j^u [c_j^u, h_j^u, b_j, L_j]$, where

$$c_j^u = c_j + \sum_{k=2}^j \left(c_{k-1} \left(\alpha^{\tau_{[k,j]}} \right) + h_{[k,j]} \left(\sum_{i=1}^{\tau_{[k,j]}-1} \alpha^{\tau_{[k,j]}+i-1} \right) \right)$$

$$h_j^u = h_{[1,j]}$$

$$b_j = b + h_{[j+1,N]}$$

$$L_j = \tau_{[1,j]}$$



Lower-bound system



The upper-bound solution $s_j^u(t)$ can be found by solving the lower-bound system, denoted by $S_j^\ell [c_j^\ell, h_j^\ell, b_j, L_j]$, where

$$c_j^\ell = c_j + h_j \left(\sum_{i=\tau_j}^{\tau_{[1,j]}-1} \alpha^i \right)$$

$$h_j^\ell = h_j$$

$$b_j = b + h_{[j+1,N]}$$

$$L_j = \tau_{[1,j]}$$



Heuristic



- Solving a single-stage system with a weighted average of cost parameters

The heuristic solution $s_j^a(t)$ can be found by solving a single-stage system, denoted by $S_j^a[c_j^a, h_j^a, b_j, L_j]$, where

$$c_j^a = wc_j^u + (1-w)c_j^l$$

$$h_j^a = wh_j^u + (1-w)h_j^l$$

$$b_j = b + h_{[j+1,N]}$$

$$L_j = \tau_{[1,j]}$$



Performance of the heuristic under different weights



- Two-stage system, 960 stage 2 solutions

$$\epsilon = \frac{|s_2(t) - s_2^g(t)| \times 100\%}{s_2(t)}$$

w		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	Max
$b = 50$	#	88	150	217	296	360	402	411	393	346	303	250	480
	$\bar{\epsilon}(\%)$	4.14	3.27	2.53	1.83	1.21	0.81	0.73	0.86	1.35	1.74	1.97	—
$b = 15$	#	32	63	96	150	233	302	357	396	397	351	280	480
	$\bar{\epsilon}(\%)$	8.05	6.78	5.64	4.63	3.59	2.52	1.68	1.13	1.04	1.54	2.53	—
Total	#	120	213	313	446	593	704	768	789	743	654	530	960
	$\bar{\epsilon}(\%)$	6.10	5.03	4.09	3.23	2.40	1.67	1.21	1.00	1.20	1.64	2.25	—

Table 2: Number of the heuristic solutions equal to the optimal solutions under different backorder cost rates and weights.



Choosing an effective weight



$b/(b+h[1,N])$	(0, 0.85]	(0.85, 0.925]	(0.925, 0.95]	(0.95, 0.975]	(0.975, 0.99]	(0.99, 1)
w	0.9	0.8	0.7	0.6	0.5	0.4

Table 3: Selecting an effective weight based on the cost ratio.

Four-stage systems (# of s_2, s_3, s_4 solutions = 1632, 1472, 1344)

backorder cost rate	stage 2	stage 3	stage 4
$b = 15$	1.00%	1.60%	1.71%
$b = 50$	0.68%	1.14%	1.31%



Myopic solution



Let the myopic solution for $S_j^a[c_j^a, h_j^a, b_j, L_j]$ be $s_j^m(t)$

Under normal approximation, we can have a closed-form expression for $s_j^m(t)$:

$$s_j^m(t) = \lambda[t, t-L_j] + \sigma[t, t-L_j]\Phi^{-1}(\beta_j), \text{ where } \beta_j = \frac{\alpha^{L_j}b_j - c_j^a(1-\alpha)}{\alpha^{L_j}(b_j + h_j^a)}$$



Myopic solution



Let the myopic solution for $S_j^a[c_j^a, h_j^a, b_j, L_j]$ be $s_j^m(t)$

Under normal approximation, we can have a closed-form expression for $s_j^m(t)$:

$$s_j^m(t) = \lambda[t, t - L_j] + \sigma[t, t - L_j]\Phi^{-1}(\beta_j), \text{ where } \beta_j = \frac{\alpha^{L_j} b_j - c_j^a(1 - \alpha)}{\alpha^{L_j}(b_j + h_j^a)}$$

The local base-stock level at stage j can be approximated as

$$\begin{aligned} s_j^{m'}(t) &= s_j^m(t) - s_{j-1}^m(t) \\ &= \underbrace{\lambda[t - L_{j-1} - 1, t - L_j]}_{\text{pipeline inventory}} + \underbrace{\sigma[t, t - L_j]\Phi^{-1}(\beta_j) - \sigma[t, t - L_{j-1}]\Phi^{-1}(\beta_{j-1})}_{\text{safety stock}} \end{aligned}$$



Near-optimal coordination scheme



- The optimal solution is time-varying, so in general, it is very difficult to design a contract to coordinate a decentralized control system
 - E.g., Donohue (2000), Parker and Kapuscinski (2008)
- Such a contract, if it existed, would have non-stationary parameters
 - Difficult to implement
- The “separation” feature of our heuristic can lead to a simple time-consistent coordination scheme that achieves the heuristic solution



Summary



We propose single-stage based heuristics that

- Simplify the computation
- Shorten the computation time by allowing parallel processing
- Provide analytical insights into how to manage safety stocks
- Lead to a simple, time-consistent contract that enables a decentralized supply chain to achieve the heuristic solution

Extensions & Future Research Directions



- Assembly systems
- Distribution systems
- Non-stationary demand with fixed batch sizes
- Assemble-to-order systems
- General networks
- Non-stationary demand with fixed reorder intervals
- Supply chain with financial flows [Luo & Shang 2011]