## Practical Tools for OR, ML and DS

Lectưre 9: Inventory \#3 (Q,R)-Policies il

February 18th, 2020

## EOQ model: demand occurs at a fixed known rate



## Today

## Random demand, multiple periods (non-perishable goods)

## Here's what demand looks like over time when the demand rate is random



## Recall goal: keeping costs low

We usually consider 3 kinds of costs when managing inventory:

- Holding costs
- Order costs
- Penalty costs (these were 0 in EOQ, because there were no stock-outs - we could determine exactly when to order so that inventory was always nonnegative)


## Model of random demand

$$
\begin{aligned}
\lambda_{t} & =\text { mean of demand in time } t \\
\sigma_{t}^{2} & =\text { variance of demand in time } t
\end{aligned}
$$

- Demand is independent in each time period
- These two parameters are a reasonable way to characterize demand
- Most of our analysis will assume $\lambda_{t}$ and $\sigma_{t}^{2}$ don't change with $t$. When we do this, we'll write them as $\lambda$ and $\sigma^{2}$.


## Notation

$$
\begin{aligned}
D_{t} & =\text { demand in time } t \\
C(t) & =\text { total demand by time } t \\
C(t) & =D_{1}+D_{2}+\ldots+D_{t}
\end{aligned}
$$

## Example

- Mean demand is $\lambda=30$ units per week
- Variance of the weekly demand is $\sigma^{2}=15$
- Suppose the lead time is $\tau=5$ weeks.

What is $\mathbb{E}[C(\tau)]$ ?

1. $15 \times 5=75$
2. $30 \times 5=150$
3. $15 \times 5^{2}=375$
4. $30 \times 5^{2}=750$
5. $30 / 2=15$

## Example

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- Suppose the lead time is $\tau=5$ weeks.

What is $\operatorname{Var}[C(\tau)]$ ?

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3. $15 \times 5^{2}=375$
4. $30 \times 5^{2}=750$
5. $30 / 2=15$

## $(Q, R)$ policy

- The policies we will consider are $(Q, R)$ policies.
- In a $(Q, R)$ policy, we set two parameters:
- the replenishment inventory level $R$
- the size of each replenishment order $Q$.
- The EOQ model also had these parameters In EOQ we could calculate one from the other because the demand was deterministic, and we could just aim for having 0 inventory when the new order arrived
- In the $(Q, R)$ model will set $Q$ and $R$ to deal with random demand, also including penalties for having not enough inventory


## Here's how a $(Q, R)$ policy works



## Here's how a $(Q, R)$ policy works



## Continuous review can be a lot of work in the real world

- $(Q, R)$ policies assume the inventory level is reviewed continuously
- To implement we either must have:
- A computer system with point-of-sale scanners that updates inventory levels after every sale
- A person assigned to monitor inventory every hour of every day
- As soon as we run out, we have to order more
- This can be annoying, and a lot of work


## We allow stockouts, but pay a penalty



## Intuitively, here's what we are doing when we set $Q$

 and $R$

Bigger $R$ means more inventory, and fewer stockouts


## Bigger $R$ means more inventory, and fewer stockouts



The average value of these minimum inventory values is called the "safety stock" and is indicated by "s"

More safety stock reduces stockouts.

Bigger $Q$ means more inventory and fewer orders


## Bigger $Q$ means more cycle stock and fewer orders



The inventory in excess of $s$ is called the "cycle stock"
This stock is depleted at the end of the cycle, and replenished at the beginning of the cycle

## Intuitively, here's what we are doing when we set $Q$ and $R$

- $Q$ controls the tradeoff between order frequency and average inventory levels.
If $Q$ is large, there are fewer orders and larger inventory levels.
- $R$ controls the tradeoff between inventory levels and likelihood of stockouts.
If $R$ is large, there is a low probability of stocking out, but the average inventory level will be higher.


## Intuitively, here's what we are doing when we set $Q$ and $R$

- $Q$ affects cycle stock, the inventory held to avoid excessive replenishment costs.
- $R$ affects safety stock, the inventory held to avoid stockouts.
- The EOQ model kept cycle stock but no safety stock.


## Optimizing the total cost

We will derive an expression for the expected cost per unit time in terms of our decision variables $Q$ and $R$, and then find optimal values of $Q$ and $R$ to minimize this cost.

## We'll model our cost like this

- Ordering cost: An order for $Q$ units costs $K+c Q$ (same as EOQ)
- Holding cost: Holding cost are incurred at a rate of $h$ per unit inventory per unit time (same as EOQ)
- Penalty: If we run out of inventory, we place the demand we cannot satisfy on backorder and pay a cost of $p$ for each backordered unit (this is new)

Note that when items are backordered, our inventory position is negative, and there is no holding cost

## We model our demand like this

$D_{t}=$ demand in time $t$, independent across $t$

$$
\mathbb{E}\left[D_{t}\right]=\lambda \quad(\text { same for every } t)
$$

$$
\mathbb{V} \operatorname{ar}\left[D_{t}\right]=\sigma^{2} \quad(\text { same for every } t)
$$

$$
C(t)=D_{1}+D_{2}+\ldots+D_{t}
$$

## Order Cost

- To compute the order cost, we want to know the number of orders per unit time
- This will be more complex than in EOQ because the time between orders varies


## Order Cost

- $I(t)=$ inventory on hand at time $t$
- $O(t)=$ number of orders before time $t$
- $I(t)=I(0)+Q \times O(t)-C(t)$
- $O(t)=\frac{C(t)+I(t)-I(0)}{Q}$
- $\mathbb{E}(O(t))=\frac{\lambda t+\mathbb{E}[I(t)]-I(0)}{Q}$
- $\mathbb{E}(O(t) / t)=\lambda / Q+\frac{\mathbb{E}[/(t)]-I(0)}{t Q} \rightarrow \lambda / Q($ as $t \rightarrow \infty)$
- This is the expected number of orders per unit time in the long run - we will call it the cycle frequency We define $T=Q / \lambda$ and call it the (expected) cycle period or cycle length


## Expected Order Cost per Unit Time

Each cycle requires one order, and has a cost of $K+c Q$.
Therefore, the expected cost of ordering per unit time is

$$
(K+c Q) \times(\lambda / Q)=K \lambda / Q+c \lambda
$$

## Expected Holding Cost per Unit Time



We'd like to compute the average inventory under this curve

## Expected Holding Cost per Unit Time



This is what it would look like if demand were deterministic

## Expected Holding Cost per Unit Time



The average height of the curve during each cycle would be Q/2 + s

## Expected Holding Cost per Unit Time



The long-run average inventory level would be Q/2 + s

## Expected Holding Cost per Unit Time



Amazingly enough, the long-run average inventory level is also $Q / 2+s$ when demand is stochastic

Knowing why is outside of the scope of this course.

## What is the safety stock?

What is the safety stock $s$ ?

1. $R-\lambda T$
2. $Q-\lambda T$
3. $R-\lambda \tau$
4. $Q-\lambda \tau$
5. $Q / 2$


## Expected Holding Cost per Unit Time

The (long-run) average inventory level is:

$$
s+\frac{Q}{2}=R-\lambda \tau+\frac{Q}{2} .
$$

## Expected Holding Cost per Unit Time

- Next, we find the expected holding cost per unit time by multiplying the long-run average inventory by the holding cost per unit and per unit time.
- The problem is that we have not restricted the inventory to positive values, and our next step assumes positive values of inventory at all times!
- However, stockouts and the resulting backorders are usually rare, so this approximation is not likely to result in major errors.


## Expected Holding Cost per Unit Time



Our approximation to holding cost assumes we pay negative holding costs here, where we actually pay 0 holding costs.

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## Expected Holding Cost per Unit Time

$$
h\left(R-\lambda \tau+\frac{Q}{2}\right)^{+} \approx h\left(R-\lambda \tau+\frac{Q}{2}\right)
$$

Our approximation to holding cost will be good enough because we will allow only a small number of stockouts.

## Stockout Cost

- While we allow backorders, they are undesirable and we should limit them.
- To do this, we include a penalty cost in the model for each stockout.
- Each unit of demand that cannot be met from stock will incur a penalty cost of $p$.


## How many stockout incidences we expect to see (per unit time)?

- We are exposed to stockout risk during the lead time.
- Before placing the replenishment order, we have at least $R$ units in stock, and there is no risk of running out.
- Once the replenishment order is placed, we know that we will have to wait a known and fixed amount of time before any more stock comes in. We get a stockout if the demand over the lead time exceeds the reorder quantity $R$.


## Stockout Cost

- Let $N$ be the number of items short in a particular cycle.
- We emphasize that $N$ is a function of $R$ by writing it as $N(R)$.
- Let $t$ be the time when inventory hits $R$ in this cycle.
- $S=D_{t+1}+D_{t+2}+\ldots+D_{t+\tau}$ is the demand during the lead time in this cycle
- $N(R)=\max \{S-R, 0\}=(S-R)^{+}$(for this particular cycle)


## Stockout Cost

- Assuming demand is independent and identically distributed (over time), we have $S=C(\tau)$ (the total amount of demand in $\tau$ time units)
- Now we can talk about the expected number of stock outs in any cycle (because demand is time independent). We denote this by $n(R)$ :

$$
n(R)=\mathbb{E} N(R)=\mathbb{E}\left[(S-R)^{+}\right]=\mathbb{E}\left[(C(\tau)-R)^{+}\right]
$$

- So the expected number of units short per unit time is $n(R) / \mathbb{E}($ length of a cycle $)=$


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- So the expected number of units short per unit time is $n(R) / \mathbb{E}($ length of a cycle $)=n(R) / T=$ $n(R) /(Q / \lambda)=\lambda n(R) / Q$
- Stockout cost: penalty for a stockout is $p$ per unit.
- Thus, the expected total stockout cost per unit time is

$$
\frac{p \lambda n(R)}{Q}
$$

## Total Cost

The total cost per unit time is found by summing the previous expressions:
$G(Q, R)=$

expected order cost per unit time

expected holding cost per unit time $(\approx)$

expected stockout cost per unit time

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expected order cost per unit time
expected holding cost per unit time $(\approx)$

expected stockout cost per unit time

This is what we want to minimize

## Total Cost

The total cost per unit time is found by summing the previous expressions:
$G(Q, R)=\underbrace{\frac{K \lambda}{Q}+c \lambda}_{\text {expected order cost per unit time }}$
$+\quad \underbrace{h\left(R-\lambda \tau+\frac{Q}{2}\right)}$
expected holding cost per unit time $(\approx)$ $+\underbrace{\frac{p \lambda n(R)}{Q}}$
expected stockout cost per unit time

This is what we want to minimize
The decision variables are $Q$ and $R$

## Optimizing $G(Q, R)$

Find critical points: $\frac{\partial G(Q, R)}{\partial Q}=0$ and $\frac{\partial G(Q, R)}{\partial R}=0$.
This will be a minimizer, because the cost is convex (no proof).

## Optimizing $G(Q, R)$

$$
\begin{aligned}
G(Q, R)= & \frac{K \lambda}{Q}+c \lambda+h\left(R-\lambda \tau+\frac{Q}{2}\right) \\
& +\frac{p \lambda n(R)}{Q} \\
\frac{\partial G(Q, R)}{\partial R}= &
\end{aligned}
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& +\frac{p \lambda n(R)}{Q} \\
\frac{\partial G(Q, R)}{\partial R}=h & +\frac{p \lambda}{Q} \frac{d n(R)}{d R}
\end{aligned}
$$

What is $\frac{d n(R)}{d R} ?$
Recall: $n(R)=\mathbb{E}\left[(C(\tau)-R)^{+}\right]$

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Recall: $n(R)=\mathbb{E}\left[(C(\tau)-R)^{+}\right]$

$$
\begin{aligned}
\frac{d n(R)}{d R} & =\frac{d}{d R} \mathbb{E}\left[(C(\tau)-R)^{+}\right] \\
& =\mathbb{E}\left[\frac{d}{d R}(C(\tau)-R)^{+}\right] \text {(under certain assumptions) } \\
& =\mathbb{E}\left[-\mathbb{1}_{\{C(\tau)>R\}}\right] \\
& =-\mathbb{P}(C(\tau)>R) \\
& =-(1-F(R)) \\
& =F(R)-1
\end{aligned}
$$

where $F(\cdot)$ is the cdf of $C(\tau)$, i.e., $F(x)=\mathbb{P}(C(\tau) \leq x)$.

## Optimizing $G(Q, R)$

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\begin{aligned}
G(Q, R)= & \frac{K \lambda}{Q}+c \lambda+h\left(R-\lambda \tau+\frac{Q}{2}\right) \\
& +\frac{p \lambda n(R)}{Q} \\
\frac{\partial G(Q, R)}{\partial R}=h & +\frac{p \lambda}{Q} \frac{d n(R)}{d R} \\
=h & +\frac{p \lambda}{Q}(F(R)-1) .
\end{aligned}
$$

## Optimizing $G(Q, R)$

$$
\frac{\partial G(Q, R)}{\partial R}=h+\frac{p \lambda}{Q}(F(R)-1)
$$

So $\frac{\partial G(Q, R)}{\partial R}=0$ means $R$ is so that

$$
F(R)=-h \frac{Q}{p \lambda}+1
$$

## Optimizing $G(Q, R)$

When we know the inverse of $F(x)=\mathbb{P}(C(\tau) \leq x)$, then we have an explicit expression for $R$ such that $\frac{\partial G(Q, R)}{\partial R}=0$ :

$$
R=F^{-1}\left(1-h \frac{Q}{p \lambda}\right)
$$

## Optimizing $G(Q, R)$

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$$
R=F^{-1}\left(1-h \frac{Q}{p \lambda}\right)
$$

provided we know $Q$.

## Optimizing $G(Q, R)$

When we do not know the inverse of $F(x)=\mathbb{P}(C(\tau) \leq x)$, then we can still use bisection search to find $R$ such that

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F(R)=1-h \frac{Q}{p \lambda}
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## Optimizing $G(Q, R)$

Find critical points: $\frac{\partial G(Q, R)}{\partial Q}=0$ and $\frac{\partial G(Q, R)}{\partial R}=0$.

## Optimizing $G(Q, R)$

$$
\begin{aligned}
G(Q, R)= & \frac{K \lambda}{Q}+c \lambda+h\left(R-\lambda \tau+\frac{Q}{2}\right) \\
& +\frac{p \lambda n(R)}{Q} \\
\frac{\partial G(Q, R)}{\partial Q}= &
\end{aligned}
$$

## Optimizing $G(Q, R)$

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\begin{aligned}
G(Q, R)= & \frac{K \lambda}{Q}+c \lambda+h\left(R-\lambda \tau+\frac{Q}{2}\right) \\
& +\frac{p \lambda n(R)}{Q} \\
\frac{\partial G(Q, R)}{\partial Q}=- & \frac{K \lambda}{Q^{2}}+\frac{h}{2}-\frac{p \lambda n(R)}{Q^{2}}
\end{aligned}
$$

## Optimizing $G(Q, R)$

$$
\frac{\partial G(Q, R)}{\partial Q}=-\frac{K \lambda}{Q^{2}}+\frac{h}{2}-\frac{p \lambda n(R)}{Q^{2}}=0
$$

## Optimizing $G(Q, R)$

$$
\frac{\partial G(Q, R)}{\partial Q}=-\frac{K \lambda}{Q^{2}}+\frac{h}{2}-\frac{p \lambda n(R)}{Q^{2}}=0
$$

Solving for $Q$ :

$$
Q^{2}=\frac{2}{h}(K \lambda+p \lambda n(R))
$$

So

$$
Q=\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
$$

## Optimizing $G(Q, R)$

$$
\frac{\partial G(Q, R)}{\partial Q}=-\frac{K \lambda}{Q^{2}}+\frac{h}{2}-\frac{p \lambda n(R)}{Q^{2}}=0
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Solving for $Q$ :

$$
Q^{2}=\frac{2}{h}(K \lambda+p \lambda n(R))
$$

So

$$
Q=\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
$$

provided we know $R$ (or more precisely $n(R)$ ).

## Optimizing $G(Q, R)$

Want $Q$ and $R$ so that

$$
\begin{aligned}
F(R) & =1-h \frac{Q}{p \lambda} \\
Q & =\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
\end{aligned}
$$

are true simultaneously.

## Optimizing $G(Q, R)$

Want $Q$ and $R$ so that

$$
\begin{aligned}
F(R) & =1-h \frac{Q}{p \lambda} \\
Q & =\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
\end{aligned}
$$

are true simultaneously.
Solve iteratively!

## Optimizing $G(Q, R)$

Want $Q$ and $R$ so that

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\begin{aligned}
F(R) & =1-h \frac{Q}{p \lambda} \\
Q & =\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
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$$

Start with $Q_{0}=\sqrt{\frac{2 K \lambda}{h}}$.

## Optimizing $G(Q, R)$

Want $Q$ and $R$ so that

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\begin{aligned}
F(R) & =1-h \frac{Q}{p \lambda} \\
Q & =\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
\end{aligned}
$$

Start with $Q_{0}=\sqrt{\frac{2 K \lambda}{h}}$.
Find $R_{0}$ so that

$$
F\left(R_{0}\right)=1-h \frac{Q_{0}}{p \lambda}
$$

(using bisection search, or $F^{-1}$ if you know it.)

## Optimizing $G(Q, R)$

Want $Q$ and $R$ so that

$$
\begin{aligned}
F(R) & =1-h \frac{Q}{p \lambda} \\
Q & =\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
\end{aligned}
$$

Calculate $Q_{1}=\sqrt{\frac{2}{h}\left(K \lambda+p \lambda n\left(R_{0}\right)\right)}$.

## Optimizing $G(Q, R)$

Want $Q$ and $R$ so that

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\begin{aligned}
F(R) & =1-h \frac{Q}{p \lambda} \\
Q & =\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
\end{aligned}
$$

Calculate $Q_{1}=\sqrt{\frac{2}{h}\left(K \lambda+p \lambda n\left(R_{0}\right)\right)}$.
Find $R_{1}$ so that

$$
F\left(R_{1}\right)=1-h \frac{Q_{1}}{p \lambda}
$$

(using bisection search, or $F^{-1}$ if you know it.)

## Optimizing $G(Q, R)$

Want $Q$ and $R$ so that

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\begin{aligned}
F(R) & =1-h \frac{Q}{p \lambda} \\
Q & =\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
\end{aligned}
$$

Calculate $Q_{2}=\sqrt{\frac{2}{h}\left(K \lambda+p \lambda n\left(R_{1}\right)\right)}$.

## Optimizing $G(Q, R)$

Want $Q$ and $R$ so that

$$
\begin{aligned}
F(R) & =1-h \frac{Q}{p \lambda} \\
Q & =\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
\end{aligned}
$$

Calculate $Q_{2}=\sqrt{\frac{2}{h}\left(K \lambda+p \lambda n\left(R_{1}\right)\right)}$.
Find $R_{2}$ so that

$$
F\left(R_{2}\right)=1-h \frac{Q_{2}}{p \lambda}
$$

(using bisection search, or $F^{-1}$ if you know it.)

## Optimizing $G(Q, R)$

Want $Q$ and $R$ so that

$$
\begin{aligned}
F(R) & =1-h \frac{Q}{p \lambda} \\
Q & =\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
\end{aligned}
$$

Calculate $Q_{3}=\sqrt{\frac{2}{h}\left(K \lambda+p \lambda n\left(R_{2}\right)\right)}$.

## Optimizing $G(Q, R)$

Want $Q$ and $R$ so that

$$
\begin{aligned}
F(R) & =1-h \frac{Q}{p \lambda} \\
Q & =\sqrt{\frac{2}{h}(K \lambda+p \lambda n(R))}
\end{aligned}
$$

Calculate $Q_{3}=\sqrt{\frac{2}{h}\left(K \lambda+p \lambda n\left(R_{2}\right)\right)}$.
Find $R_{3}$ so that

$$
F\left(R_{3}\right)=1-h \frac{Q_{3}}{p \lambda}
$$

(using bisection search, or $F^{-1}$ if you know it.)

## Optimizing $G(Q, R)$

Etcetera! Keep going around in circles!


## Optimizing $G(Q, R)$

Stop when $Q_{n+1} \approx Q_{n}$ and $R_{n+1} \approx R_{n}$ (up to some specified accuracy)

## Done!

We developed a method to find optimal $Q$ and $R$ in this model, with assumptions

- Holding costs: rate of $h$
- Order costs: fixed component $K$ and variable component c
- Penalty costs: per unit stock out


## Done?

We developed a method to find optimal $Q$ and $R$ in this model, with assumptions

- Holding costs: rate of $h$
- Order costs: fixed component $K$ and variable component c
- Penalty costs: per unit stock out

How to specify $p$ ?

