TLDR (Too Long, Didn't Read)

For pandemic PPE stockpiles, use the Newsvendor model to initialize supply and a modified continuous review policy based on the derivative of preceding demand. Our framework considers rapid fluctuations in costs, replenishment time, and demand. Appendix A is an interactive prototype using gloves during COVID-19 as an example.

Background

The Humanitarian Supply Chain Lab at the Massachusetts Institute of Technology ("MIT") has supported the Massachusetts Department of Public Health ("Department of Public Health") in simulating the state's demand for personal protective equipment ("PPE") across multiple pandemic scenarios. Following the COVID-19 pandemic, there remains significant ambiguity on how supply chain managers should translate these demand findings into a robust inventory management plan for their emergency stockpiles in the event of another pandemic.

Objective

The objective of this research is to develop an inventory policy framework that can best meet uncertain pandemic demand, yet is flexible for undetermined future diseases. A key challenge with forecasting pandemic PPE demand is the non-independently and non-identically distributed ("non-i.i.d.") nature of pandemic waves. Therefore, such policies should be dynamic enough to respond to rapid changes in demand while minimizing the excess holding costs of oversupply, or worse, the life-threatening costs of undersupply.

Considering the high level of uncertainty during pandemics, our proposal omits specific quantifiable recommendations outside a COVID-19 scenario; rather, it provides a viable framework that can be adjusted accordingly within unique pandemic scenarios.

Analysis

Residual data leveraged for this research includes daily PPE demand from the Department of Public Health, anonymized hospital orders from Massachusetts General Hospital ("MGH") including timing and magnitude during COVID-19, and simulated PPE demand using Monte Carlo simulation from MIT[1].

The data was graphed in *Figure 1* to visualize the behavior of the five commodities: gloves, gowns, eye protection, N95 masks, and surgical masks. Given their highly variable and extreme values, we normalized the data using the mean residual multiplier ("MRM"), defined as the value of residual demand at the current time step divided by the mean for the entire time period considered.

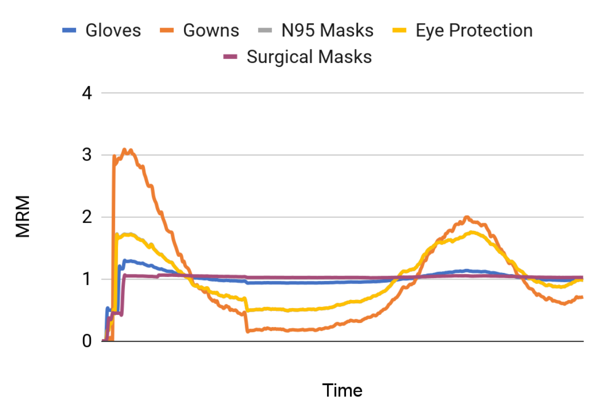

Figure 1: COVID-19 Residual Demand (MRM)

Our initial analysis revealed two notable insights. First, the commodities followed similar

---

[1] Goentzel, Finegan, McGuigan, "Preparing PPE stockpiles for the next pandemic", MIT Humanitarian Lab. 5 January 2022.

synchronous ordering patterns. Gloves and masks, for instance, had almost identical demand. We hypothesized that these units were ordered as kits and therefore had the same replenishment cycles. We will be using gloves as an example.

Gowns had the most variability with an MRM exceeding on average 1.00 and in some cases reaching even above 3.00. No other commodity demonstrated this level of intensity.

Model

Our framework uses a combination of the Newsvendor model for the initial period of demand, followed by a modified continuous review policy for non-i.d.d. demand. The model also makes some intrinsic assumptions specific to a COVID-19 scenario:

1. Consensus from interviews conducted by the MIT Center for Logistics and Transportation ("CTL") determined a lead time of 8 weeks to receive orders of PPE after placing an order during the first months of the pandemic.

2. During the initial stages of the pandemic, prices for PPE increased by around 400%[2], therefore assuming new price are fivefold the prices in normal conditions.

Initial Period

To initialize the pandemic preparedness stock, we applied a Newsvendor model to cover the commencing period prior to the pandemic when elevated stock levels are not readily available. We incorporated these assumptions on overstocking and understocking costs based on these figures. As such, we suggest applying a Newsvendor policy to determine the initial stockpile. Following our assumptions, we use a critical ratio of 0.80, for a 400% mark-up for our initial stockpile calculation.

Pandemic Period

After establishing the stockpile amount for our assumed time period, our research proposes a modified continuous review policy that relies on the derivative of the preceding historical demand to determine the cycle service level ("CSL") and economic order quantity ("Q"). As the reorder point ("*s*") changes with increasing or decreasing CSL, orders at these points will equal Q + Δ*s*.

In essence, the most recent rate of change for the demand will determine the safety factor and inventory trigger point for stockpile replenishment. Our model also considers relevant variables such as lead time, inventory costs, and holding costs. In practice, this event-based periodic review policy responds best to waves in demand, be it a rapid increase or decrease. It also reduces reliance on administrative costs as it does not require period review of inventory levels by staff, provided that outgoing orders are automatically tracked and reported into a centralized supply database.

To illustrate this framework, we use gloves in a simulated pandemic as a prototype, although the same model would work across all commodities. We calculate the derivative of this graph using the preceding period of one day prior, as illustrated in Figure 2. Formulaically:

$$\frac{\delta D}{\delta T} = \frac{D_2 - D_1}{T_2 - T_1}$$

[2] U.S. Department of Justice, "Brooklyn Company Admits Price Gouging KN95 Masks During COVID-19 Pandemic". Accessed 28 April 2022

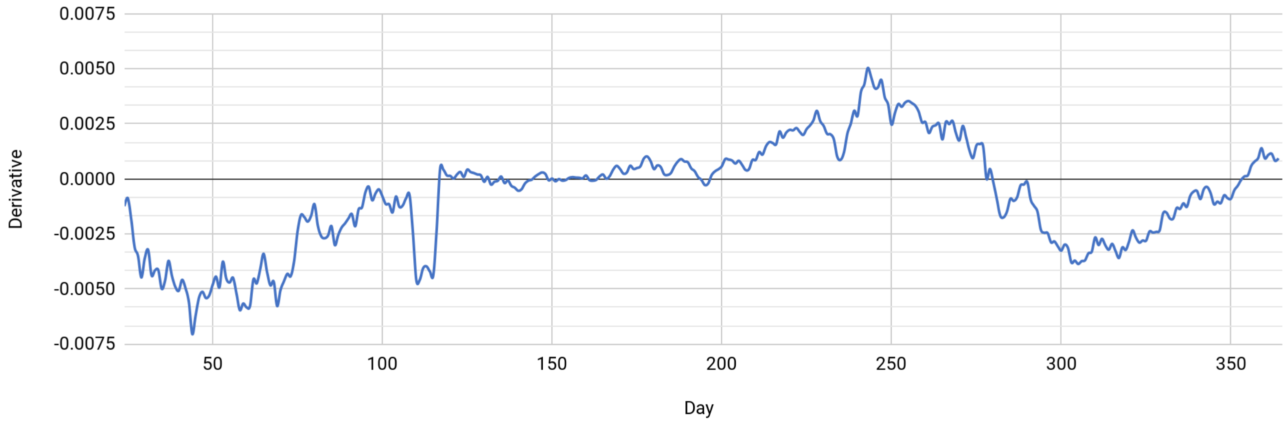

Figure 2: Derivative of Gloves, Residual Demand, Day 25-365

where D_2 is the demand at the end of T_2 and D_1 is the demand at the beginning of T_1, in individual units and days, respectively.

The resulting derivative for gloves gives slope values as high as 0.2116 during the first month and 0.0050 thereafter, signifying the rate of change reach material magnitudes. Using the derivative, we categorize the slope x into five intervals:

$[a, b)$		
-0.0010	,	-0.0005
-0.0005	,	0.0000
0.0000	,	0.0025
0.0025	,	0.0050
0.0050	,	0.0100

where $[a, b) = \{ x \in \mathbb{R} \mid a \le x < b \}$.

Negative values indicate a drop in PPE demand, and conversely, positive values indicate an increase in PPE demand. Each interval indicates the rate of change, with [–0.0005, 0.0005) being no change for practical purposes, and [0.0005, 0.0100) denoting the greatest rate of change. These figures also parallel daily reported cases of

COVID-19, as derived from the historical numbers published by state and local health agencies (cases, deaths) and the U.S. Department of Health and Human Services (tests, hospitalizations, I.C.U. patients)[3]. Although cases are out of scope for this model, it is worthwhile considering reported cases as an earlier trigger to the inventory policy model.

We incorporate these intervals into the continuous review policy, where each provides the k and CSL values. For instance, a rate of change of 0.0750 will fall within the highest band, therefore triggering the highest k and CSL, 3.7190 and 0.9999 respectively.

Using gloves during COVID-19 as an example, our model proposes the following continuous inventory policy outlined in *Table 1*:

[3] The New York Times, "Tracking Coronavirus in Massachusetts". Accessed 3 May 2022.

Derivative	**CSL**	***k***
[–0.0010, –0.0005)	0.0085	1.0364
[–0.0005, 0.0000)	0.9000	1.2816
[0.0000, 0.0025)	0.9500	1.6449
[0.0025, 0.0050)	0.9800	2.0537
[0.0050, 0.0100)	0.9999	3.7190

Table 1: Continuous Review Policy, Gloves, COVID-19 Demand

All said, our model can be applied to different pandemic situations. The most basic input variables that must be known is the rate of change for demand. All other variables, including costs, can be assumed based on historical or market data.

Conclusion

In conclusion, we recommend the following steps to develop an inventory policy framework that can best meet uncertain pandemic demand:

1. Apply a Newsvendor model at the beginning of a pandemic to determine stockpile levels for the stocks that covers demand until the initial replenishment is received.

2. Determine the rate of change (i.e., derivative) of the preceding demand using one, three, or seven day periods depending on the severity of the pandemic.

3. Adopt a continuous review policy to determine the economic ordering quantity "Q" when stockpile levels reach a critical low point "s".

4. Depending on the rate of change, the threat level will determine the cycle service level and safety factor *k*. Refer to Table 1 as an example.

We provided a prototype calculator in Appendix A that can be used for varying pandemic situations, provided the key input variables are known values.

Appendix

A. [Pandemic Stockpile Calculator]