

Demand forecasting by temporal aggregation

The Impact on Supply Chain Cost

Bahman Rostami-Tabar ¹ Stephen M. Disney ¹

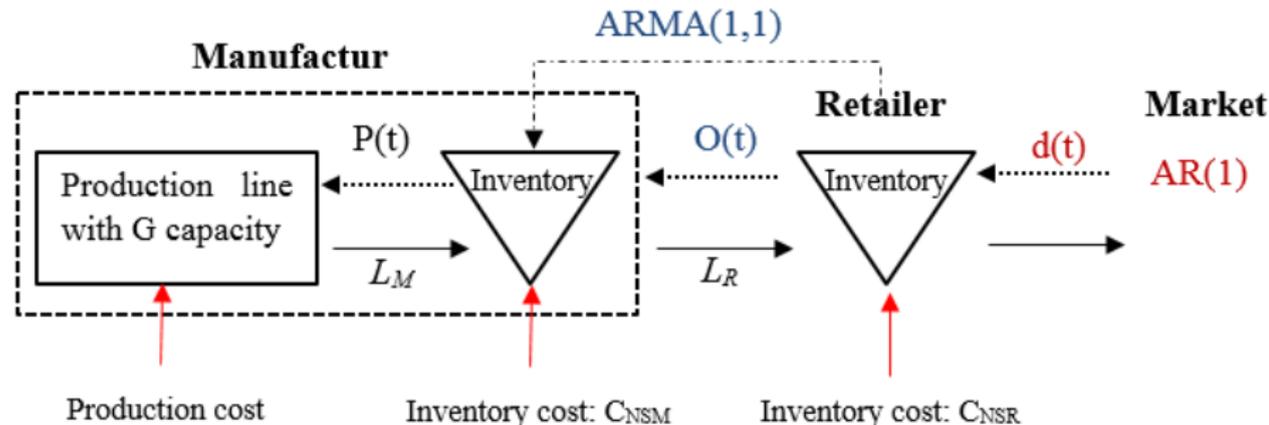
¹Logistics System Dynamics Group, Cardiff Business School, Cardiff University,
Aberconway Building, Colum Drive, CF10 3EU, United Kingdom.

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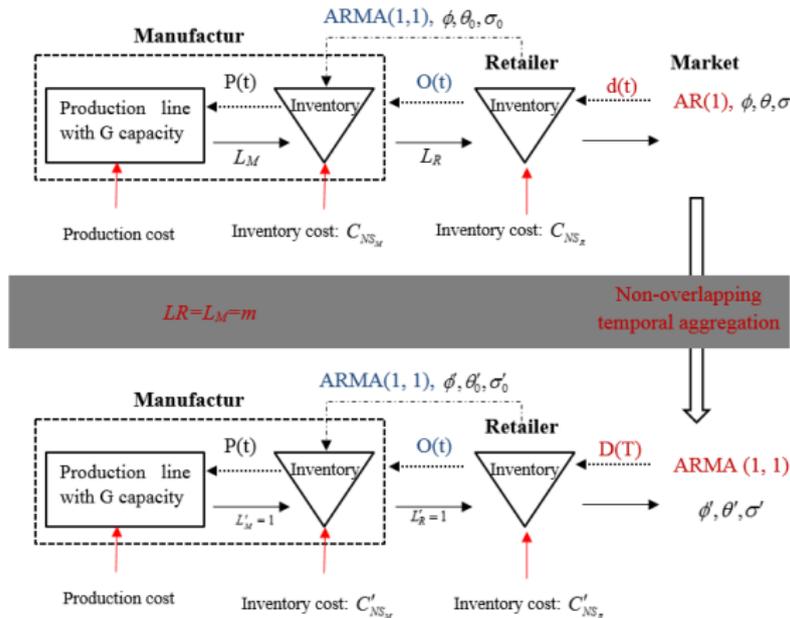
Supply Chain Model

- Minimizing the cost across the supply chain is one of the main concerns of SC managers.
- One typical approach is to minimize the forecast error and consequently reduce unnecessary stock costs.



Problem

Should we use disaggregate or aggregated demand data in forecast in a SC setting?



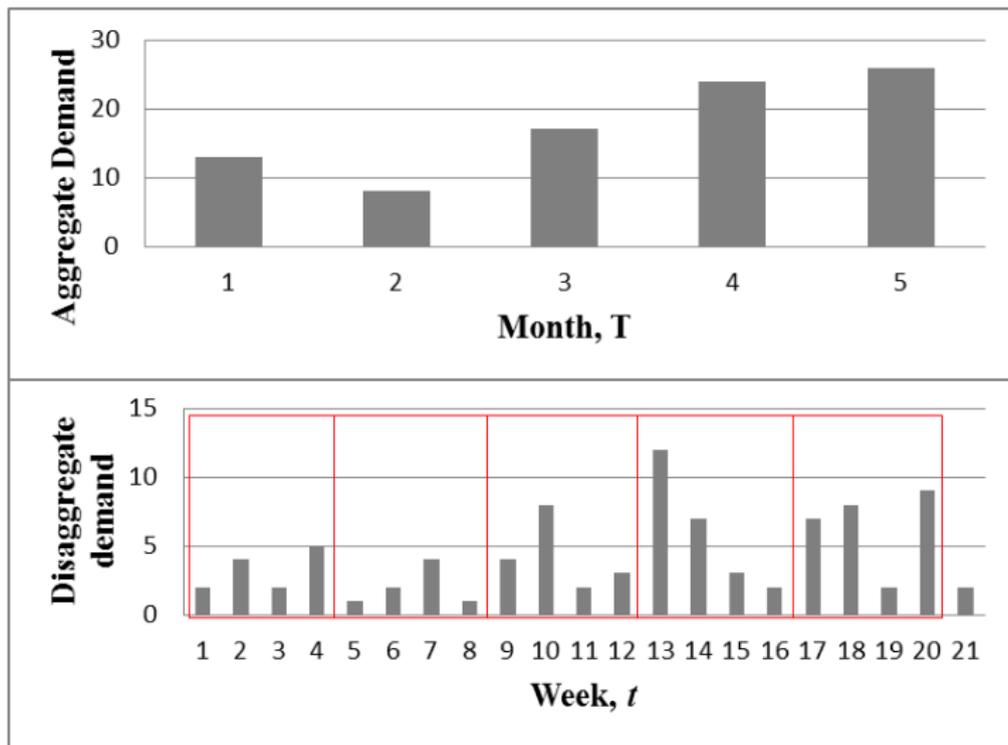
Motivations for the current study

- Recent advances have demonstrated the benefits of temporal aggregation for demand forecasting, including increased accuracy, improved stock control and reduced modeling uncertainty [Nikopoulos et al. (2011), Babai et al. (2012), Rostami-Tabar(2013, 2014), Kourentzes et al. (2017)].
- Substantial part of the literature in TA is dedicated to the impact of TA on forecast accuracy both empirically and analytically.
- There is a lack of analytical investigation on conditions under which TA can reduce supply chain costs.

Our contribution

- We develop the variance and cost of inventory for a two echelon SC when the aggregated demand is used.
- We investigate the impact of the auto-regressive process parameter and the lead time/aggregation level on the variance and cost of inventory.
- We compare and contrast our results when aggregated demand is used in OUT policy to the case of using disaggregate demand.

Non-overlapping temporal aggregation



Assumptions

- Data Generation Process: AR(1)

$$d(t) = C + \phi d(t-1) + \epsilon(t), \epsilon(t) \sim N(0, \sigma^2),$$

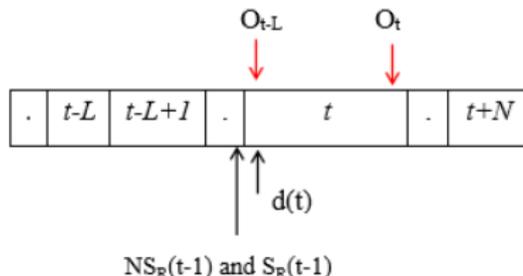
- Forecasting method: Minimum Mean Squared Error (MMSE)

$$\hat{d}_{t+i} = E(d_{t+i} | d_t, d_{t-1}), i = 1, 2, \dots$$

- Inventory policy: OUT level policy.

Sequence of events

- 1 Inventory level at period $t - 1$, $S_R(t - 1)$ is observed.
- 2 Net stock at period $t - 1$, $NS_R(t - 1)$ is observed.
- 3 The order placed at period $(t - L)$ is received, $O(t - L)$.
- 4 Demand, $d(t)$ is satisfied from the stock.
- 5 The order $O(t)$ is calculated at the end of period t .
- 6 $NS_R(t)$ and consequently the amount of backorder $NS_R(t)^-$ and inventory $NS_R(t)^+$ are updated at the end of period t .
- 7 The cost is calculated for period t .



Ordering policy and cost at retailer

$$C_{NS_R} = h_R \times E(NS_R(t)^+) + b_R \times E(NS_R(t)^-)$$

$$NS_R(t)^+ = \max(0, NS_R(t))$$

$$NS_R(t)^- = \max(0, -NS_R(t))$$

$$NS_R(t) = NS_R(t-1) + O(t - L_R) - d(t)$$

$$O(t) = d(t) + S_R(t) - S_R(t-1)$$

$$S_R(t) = \hat{d}_{L_R}(t) + z_R \sigma_{NS_R}$$

Lead time forecast and inventory variance

$$\hat{d}_{L_R}(t) = E \left(\sum_{i=1}^{L_R} d(t+i) | d(t), d(t-1), \dots \right) = \frac{1 - \phi^{L_R}}{1 - \phi} (\phi d(t) - \theta \epsilon_t)$$

$$\begin{aligned} \sigma^2_{NSR} &= E \left(\text{Var} \left(\sum_{i=1}^{L_R} d(t+i) - \hat{d}_{L_R}(t) \right) \right) \\ &= \frac{L_R (\theta - 1)^2 (\phi^2 - 1) + (\phi - \theta) (\phi^{L_R} - 1) (\theta (1 + 2\phi - \phi^{L_R}) + \phi (\phi^{L_R} - 1) - 2)}{(\phi - 1)^3 (1 + \phi)} \sigma_\epsilon^2 \end{aligned}$$

Relationship between aggregated and dis-aggregated parameters

The m periods non-overlapping aggregated demand ($m = \text{leadtime}$), $D(T)$ can be expressed as a function of the non-aggregated demand series as follows

$$D(T + 1) = \sum_{i=1}^m d(t + i),$$

$$D(T - k) = \sum_{i=1}^m d(t - i + k),$$

- The aggregated process of AR(1) is an ARMA(1,1) with
- $D(T + 1), D(T), \dots$ follows an ARMA(1,1) with ϕ', θ' and σ'

Relationship between aggregated and dis-aggregated parameters

$$\phi' = \phi^m$$

$$\theta' = \begin{cases} \frac{-(X + \phi^{2m} X - 2\phi^m) + \sqrt{(X + \phi^{2m} X - 2\phi^m)^2 - 4(1 - \phi^m X)^2}}{2(1 - \phi^m X)}, & \phi > \theta \\ \frac{-(X + \phi^{2m} X - 2\phi^m) - \sqrt{(X + \phi^{2m} X - 2\phi^m)^2 - 4(1 - \phi^m X)^2}}{2(1 - \phi^m X)}, & \phi < \theta \end{cases}$$

where

$$X = \frac{(m\gamma_0 + \gamma_1 \sum_{k=1}^{m-1} 2(m-k)\phi^k - 1)}{\gamma_1 \left(\sum_{k=1}^m k\phi^k + \sum_{k=1}^{m-1} k\phi^{2m-k} \right)},$$

$$\sigma'^2 = \frac{(1 - \phi^{2m}) \left(m\gamma_0 + \gamma_1 \sum_{k=1}^{m-1} 2(m-k)\phi^{k-1} \right)}{(1 - 2\phi^m \theta' + \theta'^2)}$$

Lead time forecast and inventory variance with aggregated data

$$\hat{d}'_{LR}(t) = E(D(T+1)|D(T), D(T-1), \dots) = (\phi' D(T) - \theta' \epsilon'_T)$$

$$\begin{aligned} \sigma_{NSR}^{2'} &= E\left(\text{var}\left(D(T+1) - \hat{d}'_{LR}(t)\right)\right) \\ &= \frac{(\theta' - 1)^2 (\phi'^2 - 1) + (\phi' - \theta') (\phi' - 1) (\theta' (1 + 2\phi' - \phi') + \phi' (\phi' - 1) - 2)}{(\phi' - 1)^3 (1 + \phi')} \sigma_{\epsilon}^{\prime 2} \end{aligned}$$

Demand process at manufacturer

- The OUT policy transforms an AR(1) demand process into the following ARMA(1,1) order process,

$$O(t+1) = C + \phi O(t) - \theta_0 \epsilon_0(t) + \epsilon_0(t+1), \epsilon_0(t) \sim N(0, \sigma_0^2),$$

$$\theta_0 = \frac{\phi(1 - \phi^{L_R})}{1 - \phi^{L_R+1}}$$

$$\epsilon_0(t) = \left(1 + \frac{\phi(1 - \phi^{L_R})}{1 - \phi} \right) \epsilon(t)$$

Ordering policy and cost at manufacturer

$$C_{NS_M} = h_M \times E(NS_M(t)^+) + b_M \times E(M(t)^-)$$

$$NS_M(t)^+ = \max(0, NS_M(t))$$

$$NS_M(t)^- = \max(0, -NS_M(t))$$

$$NS_M(t) = NS_M(t-1) + P(t - L_M) - O(t)$$

$$P(t) = O(t) + S_M(t) - S_M(t-1)$$

$$S_M(t) = \hat{O}_{L_M}(t) + z_M \sigma_{NS_M}$$

Lead time forecast and inventory variance at manufacturer with disaggregate demand

$$\hat{d}_{L_M}(t) = E \left(\sum_{i=1}^{L_M} O(t+i) | O(t), O(t-1), \dots \right) = \frac{1 - \phi^{L_M}}{1 - \phi} (\phi O(t) - \theta_0 \epsilon_{0,t})$$

$$\begin{aligned} \sigma^2_{NS_M} &= E \left(\text{Var} \left(\sum_{i=1}^{L_M} O(t+i) - \hat{O}_{L_M}(t) \right) \right) \\ &= \frac{L_M (\theta - 1)^2 (\phi - 1) + 2\phi^{L_M} (\theta - 1) (\phi - \theta) (\phi^{L_M} - 1) + \frac{(\theta - \phi)^2 \phi^{2L_M} (\phi^{2L_M} - 1)}{1 + \phi}}{(\phi - 1)^3} \sigma_\epsilon^2 \end{aligned}$$

Aggregated demand process at manufacturer

- The OUT policy transforms an aggregated ARMA(1,1) demand process into another ARMA(1,1) order process, which is

$$O(T+1) = C + \phi' O(T) - \theta'_0 \epsilon'_0(t) + \epsilon'_0(t+1), \epsilon_0(t) \sim N(0, \sigma_0^2),$$

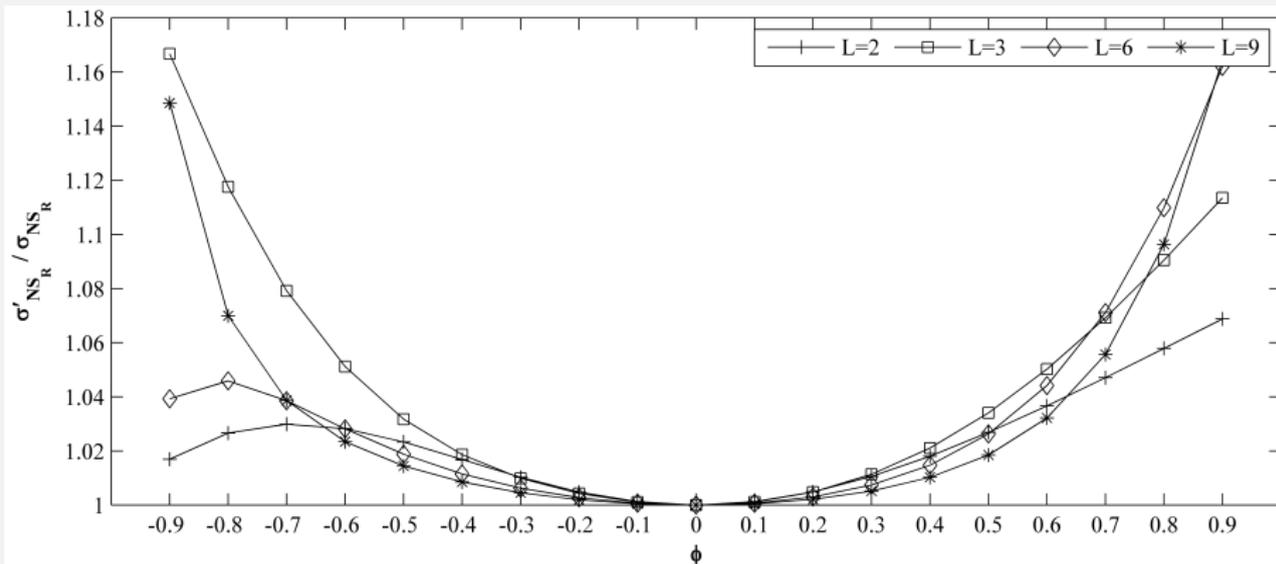
$$\theta'_0 = \frac{\phi' (1 - \phi'^{L_R})}{1 - \phi'^{L_R+1}}$$

$$\epsilon'_0(t) = \left(1 + \frac{\phi' (1 - \phi'^{L_R})}{1 - \phi'} \right) \epsilon'(t)$$

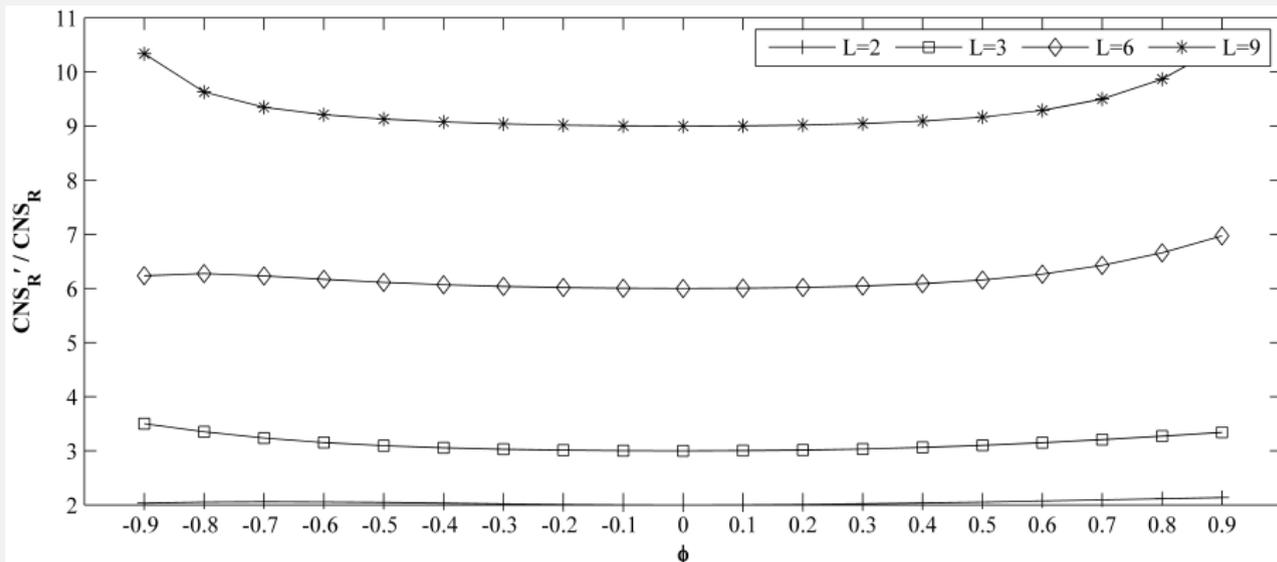
Lead time forecast and inventory variance at manufacturer with aggregated demand

$$\sigma'_{NSM}{}^2 = \frac{(\theta' - 1)^2 (\phi' - 1) + 2\phi' (\theta' - 1) (\phi' - \theta') (\phi' - 1) + \frac{(\theta' - \phi')^2 \phi'^2 (\phi'^2 - 1)}{1 + \phi'}}{(\phi' - 1)^3} \sigma'_\epsilon{}^2$$

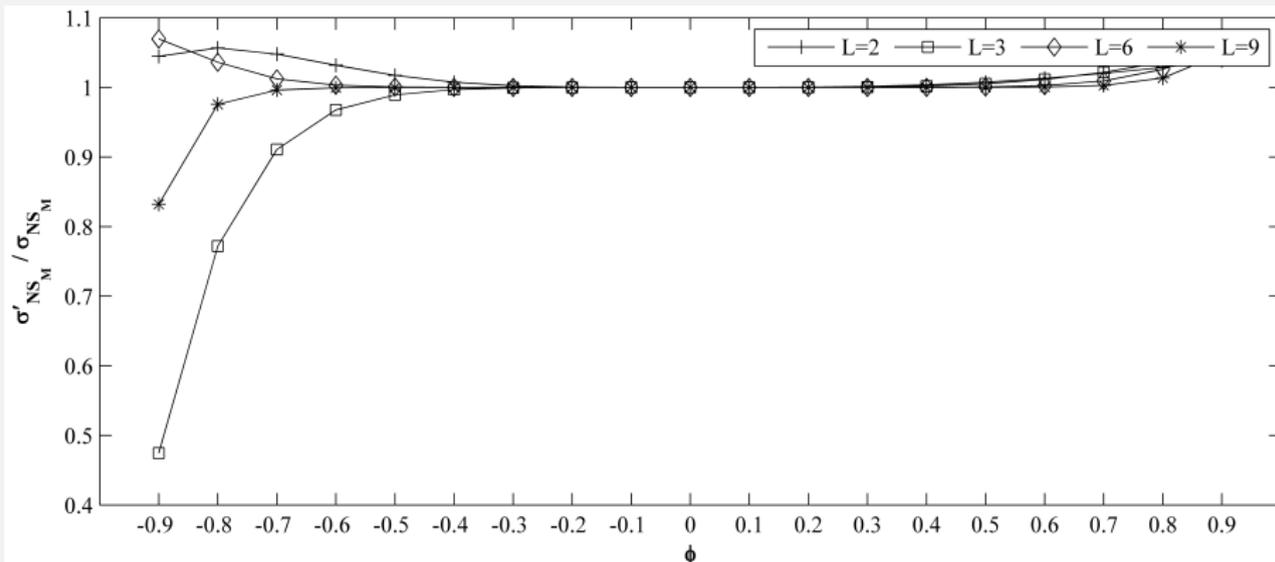
Ratio of inventory variance at retailer



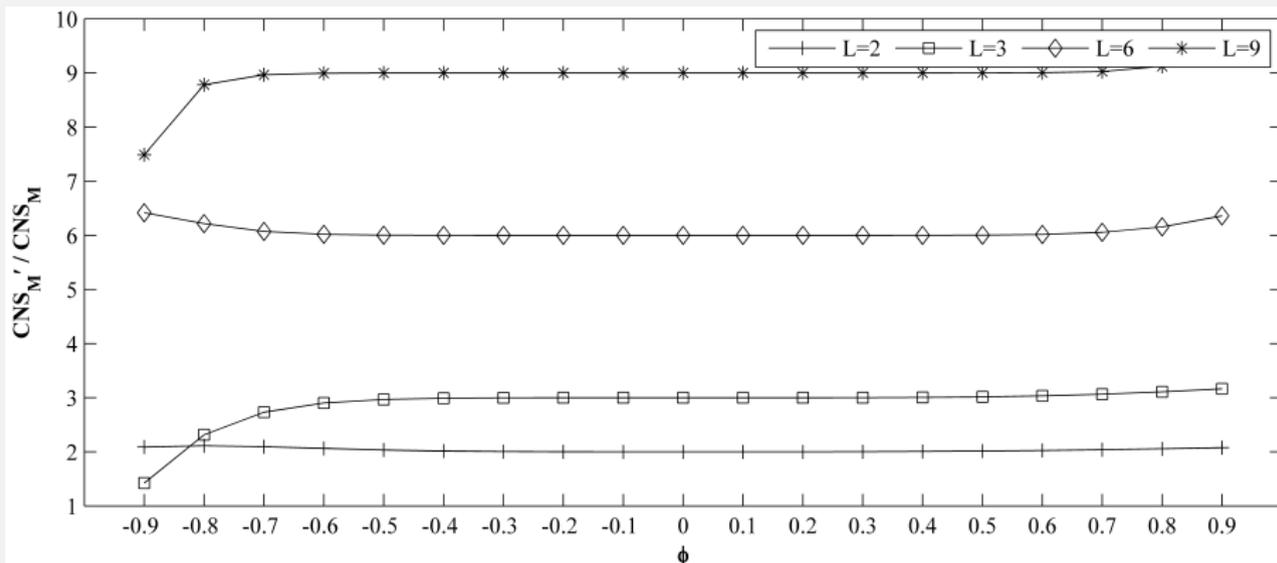
Ratio of inventory cost at retailer



Ratio of inventory variance at manufacturer



Ratio of inventory cost at manufacturer



Concluding remarks

- TA does not improve inventory variance and cost when $\phi > 0$ regardless the value lead time/aggregation level values and supply chain stage
- Inventory variance can be reduce at manufacturer level depending on the lead time/aggregation level values and only for $\phi < 0$
- TA does not improve Inventory cost at manufacturer level
- Benefits of using TA may be seen at manufacturer level with production cost.

Thank you for listening!