Interaction of optimization models and information sharing in a two echelon supply chain

by

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DEDICATION

I would like to dedicate this thesis to my parents without whose support I would not have been able to complete this work.

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ABSTRACT

Uncertainty in the manufacturing industry has been a research interest for many years. Deterministic and stochastic optimization methods have been proposed in the past. The objective of this thesis is to study the interaction of these models in a supply chain with a varying error in demand forecast. All the possible combinations of the optimization strategies in a two-echelon supply chain have been considered. Results indicate that the performance of the supply chain is driven by the choice of strategy of the supplier. Stochastic optimization is very efficient in lowering the operational costs and bull-whip effect in most cases. However, in cases where the trend in demand variation is smooth, use of deterministic strategy by both stakeholders is beneficial and it helps in lowering operational cost. Information sharing results in cost saving in most of the cases. It increases with increase in root mean squared error in demand forecast when the supplier uses deterministic strategy.

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CHAPTER 1. INTRODUCTION

Uncertainty is found in many real-life situations. In the context of manufacturing, demand is a major source of uncertainty. Transportation lead time, machine break down lead time are some other factors that affect manufacturing decision making as they have uncertainty. Decisions related to production and inventory can be made using deterministic and stochastic optimization models as discussed by (Behncke, Ehrhardt, & Lindemann, 2013).

Stochastic programming is a useful tool to mitigate uncertainty (Cunha, Raupp, & Oliveira, 2017). However, when stochastic and deterministic optimization approach are used in supply chain scheduling, their performance is similar (Sawik, 2017). Hence, it would be worth investigating the interaction of these models when they are used by the stake holders in a supply chain for production planning and inventory management. Uncertainty in a supply chain leads to bull-whip effect. Research on bull-whip effect in a supply chain under various information sharing setting has been done in the past (Ma, Wang, Che, Huang, & Xu, 2013) and it suggests that it is helpful to use the past demand / order data to forecast future demand. There are several ways of forecasting demand as discussed by (Syntetos, Babai, Boylan, Kolassa, & Nikolopoulos, 2016). However, this research studies the supply chain performance with respect to varying error magnitude in demand forecast of the downstream supplier. The upstream supplier relies on the past data to forecast the demand.

This research considers a two-echelon supply chain with demand uncertainty and looks at the effect of optimization models on manufacturing decision making. Like (Rahdar, Wang, & Hu, 2018; Váncza, Egri, & Monostori, 2008), in this thesis, a rolling horizon is considered to build the optimization model and two possible optimization strategies are used.

As this is a two-echelon supply chain, all the combinations of strategies that are possible are studied with and without information sharing. In our study we consider that the only information shared is the possible future orders as determined by the decision-making model. We also try to understand how demand uncertainty propagates along the supply chain when the stake holders use various optimization models.

In section 2 looks at the research that has been done and in section 3, the problem statement is defined. Section 4 describes the model formulation and the assumptions made in it. Then, a case study is presented in section 5 that was considered to understand the interaction of the optimization models in a two-echelon supply chain. The remainder of the thesis discusses the results and conclusion.

CHAPTER 2. LITERATURE REVIEW

Increasing competition and challenging market situations has led to research on the use of optimization techniques in manufacturing decision making as described by (Beamon, 1998; Behncke et al., 2013). Apart from optimization methods, there are various other models such as economic (Christy & Grout, 1994) and simulation models (Petrovic, 2001) which look at qualitative methods and the study of existing process characteristics to optimize the supply chain. (Mittal, 2016; Mittal & Krejci, 2018) use agent-based discrete-event simulation modelling to study warehousing operations and improve its operational planning decisions. Furthermore, Monte Carlo simulation and stochastic algorithms (Jellouli & Chatelet, 2001) have also been used in research to optimize supply chain performance. (Lee, Kim, & Moon, 2002) describes a hybrid simulation-based approach that can be used in production distribution planning. Algorithms involving hybrid computational frame work to solve network design problem and inventory control problem using simulation have been proposed by (Ye & You, 2015). (Cunico & Vecchietti, 2015; Fu & Chen, 2017; Khalili-Damghani & Ghasemi, 2016) use fuzzy programming models to deal with supply chain optimization. Some of the research is focused on specific industry like the lumber supply chain (Bajgiran, Zanjani, & Nourelfath, 2016). Similarly, (Mittal & Krejci, 2015) improve the logistics and operational efficiency of a regional food hub by proposing a hybrid simulation model of its inbound logistics.

Uncertainty in demand and lead times have been addressed in the literature by using optimization methods. (Heydari, Mahmoodi, & Taleizadeh, 2016) considers stochastic lead times in the supply chain and propose an incentive scheme to reduce shortage in the supply chain. Similarly, demand uncertainty has been modelled (Nishi & Yoshida, 2016) in a decentralized supply chain as a stochastic multi-period bi-level supply chain problem. This research considers demand uncertainty in a decentralized supply chain where the stake holders make decisions for themselves. However, both deterministic and stochastic optimization models are considered to study their interaction in this research. Demand and order quantity uncertainty is considered in production planning by constructing MILP problems and solving them by heuristics (Aouam, Geryl, Kumar, & Brahimi, 2018). In the current study, a constant batch size is considered so that the orders can be placed in multiples of the batch size. Multi-objective stochastic models studied by (Felfel, Ayadi, & Masmoudi, 2016; Ma et al., 2013; Pasandideh, Niaki, & Asadi, 2015) considering demand uncertainty is also seen in the research. However, the existing literature does not consider the interactions of optimization models in a supply chain. Hence, the main objective of this research is to consider stochastic and deterministic optimization models in a two-echelon supply chain and study their interaction when they are used by the stake holders under demand uncertainty with and without information sharing.

Bull-whip effect is caused by uncertainty in demand. Hence, forecasting is an important aspect and a focused research has been done in the past (Syntetos et al., 2016). (Sun & Ren, 2005) studied the impact of forecasting methods such as moving average, exponential smoothing, and minimum mean square error on the bull-whip effect in a two-echelon supply chain. In the current research, three demand data sets are used to study the interaction of optimization models. Good sales strategy needs to be used to control bull-whip effect (Cao, Xiao, & Sun, 2017) and information sharing with regards to the placing of future order helps improve the supply chain performance (Thonemann, 2002). However, according to (Li, 2013), information sharing in a supply chain might always not be possible and studies the optimization of supply chain under constrained information sharing. (Chenglin & Xinxin, 2009) study a news vendor model characterized by short life cycle, stochastic demand and endogenous price. They conclude that information sharing might not be feasible when demand volatility is underestimated by the retailer and not by the manufacturer. Hence, we consider limited information sharing and vary the forecasting error magnitude in demand data. This is going to help in studying the behaviour of the models without focusing on the actual forecasting method.

(Danloup, Allaoui, & Goncalves, 2013; Kumar & Pugazhendhi, 2012) have studied coordination and information sharing in a supply chain. (Chan & Chan, 2005) use economic order quantity which is a deterministic model and a coordination method to mitigate demand uncertainty through contract mechanism. Demand uncertainty leads to shortage which implies low service level and hence, to improve the service level and lower the costs, the intentions and interactions of partners in a supply chain must be managed (Váncza et al., 2008). To deal with stochastic demand, (AlDurgam, Adegbola, & Glock, 2017) proposes the use of manufacturer's production rate as a decision variable and points out that coordination between the vendor and the manufacturer is necessary for this model to sustain. By considering seasonal demand in a multi-buyer single supplier situation, (Chang & Chou, 2013) indicates that coordinated replenishment policy is beneficial when compared to independent ordering policy. Some of the authors discuss centralized optimization strategy which involves more information sharing than just demand forecast. In a three-layer supply chain joint economic lot sizing problem, (Abdelsalam & Elassal, 2014) suggests that centralized safety stock is better than decentralized policy. Flexibility delaying the production start is sometime beneficial (Shen, Lu, & Wu, 2009), however, it could be difficult to manage and sustain. In a real-world scenario, it might not always be possible to achieve this level of coordination in a supply chain. Hence, considering minimal collaboration in this research, possible future orders is the only information that the stake holders in the supply chain share.

CHAPTER 3. METHODOLOGY

Problem statement, optimization model and a case study that will be considered to evaluate the performance of the models have been described in this section. As the manufacturer and the supplier can choose to use deterministic or stochastic optimization strategy, there are four possible combinations of strategies that will be looked at in this research. With regards to the demand data, three data sets with different trend lines will be considered to know which combination of strategy is better in all the three situations. Later, the effect of information sharing on the performance of the strategy combinations is also studied and the only information that is shared is the future orders.

Problem Statement

This research deals with a two-echelon supply chain as shown in Figure 1. The demand that the manufacturer has for his products is not known perfectly to him. In real life scenario there is always uncertainty in demand. When he forecasts his demand there could be variation in the actual demand and his forecast. This variation affects his inventory, transportation, production and ordering costs for the current period.

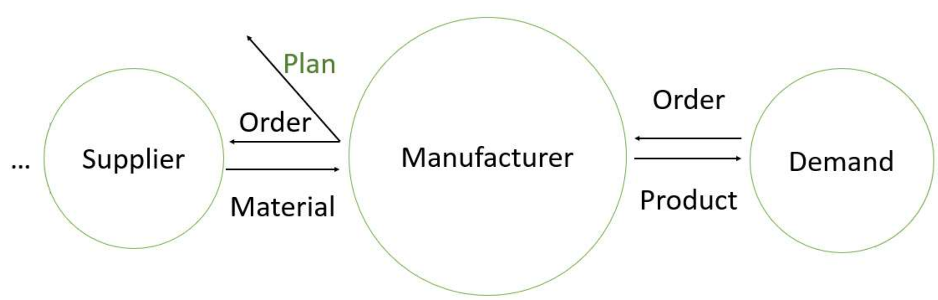

Figure 1 Supply Chain

If he produces more than the actual demand, he will have to carry extra inventory, and this leads to an increase in the costs mentioned earlier. On the other hand, if he produces less than the actual demand, he will have to bear the shortage cost. Both the situations are unfavourable, specially shortage. The ideal and the best scenario would be when he knows the future demand perfectly i.e., he has perfect information. This does not happen in real life situation and when there are many upstream suppliers, there is going to be an increase in the amplitude of the variation of the demand at every level. Hence, we need to find a way to make good decisions so that we incur least cost possible in each situation. This is possible by using optimization techniques such as deterministic and stochastic optimization.

As there are two stake holders in this research, we need to know the combination of optimization strategies that would work well for the supply chain and understand how the combinations affect the decision variables. To analyse the effect of information sharing, we consider that the manufacturer shares the possible future orders.

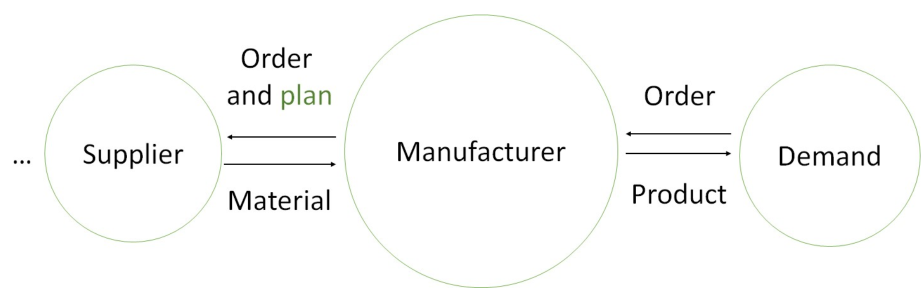

Figure 2 Information sharing in supply chain

The research questions that are addressed are as follows:

- Is stochastic optimization always beneficial?
- Should the choice of strategy depend on the trend of variation in demand data?

- Effect of error in demand data forecast on operational cost and bull-whip effect
- Effect of information sharing on the supply chain

Model formulation

In this section, we present an optimization model where we consider several scenarios of demand for the Manufacturer/Supplier using Deterministic/Stochastic programming. The parameters and variables of the model are described in detail after this.

Models for decision making

As discussed earlier, the models of decision making under uncertainty considered in this research are two. There is a difference in the way demand is forecast in these models.

- Deterministic (D) - Only one scenario of demand data is assumed to be true
- Stochastic (S) - Forecast of several scenarios of future demand weighted by assumed probabilities are considered

However, the way these optimization strategies are used by the manufacturer and the supplier is different. For the manufacturer, random error of known magnitude is added to known demand and is used as the forecast. The supplier relies on the past data to forecast the future demand. When using the deterministic strategy, the supplier assumes that a past pattern of demand would repeat and when he uses stochastic strategy, scenarios are picked from the historical data and the most recent choice of scenario from the past gets the highest weight. The farther the scenario in the past, less is the weight assigned to it.

Assumptions

- Transportation Lead time is fixed, and it is assumed that there is no uncertainty in it
- Supplier is dedicated to the manufacturer i.e. he only supplies to one manufacturer

- The manufacturers will produce a minimum number of units even if the demand is zero
- Information sharing in the context of this research means sharing the predicted future orders with the upstream suppliers

Notation

Input

- d_t: (in unit) known demand in time $t \in \{0, ..., T\}$ where T is the modelling horizon
- α: magnitude of error in demand forecast
- $R^{\alpha}_{s,t}$: random number picked from a standard normal distribution in time $t \in \{0, ..., T\}$ under scenario $s \in \{1, ..., S\}$ considering magnitude of error $\alpha \in \{0, 1000, .., 10000\}$
- $D^{\alpha}_{s,t}$: (in units) demand forecast in time $t \in \{0, ..., T\}$ under scenario $s \in \{1, ..., S\}$ considering magnitude of error $\alpha \in \{0, 1000, .., 10000\}$
- p^s: the probability of scenario *s* occurring
- ΔI_t: (in number of units) incoming materials in time $t \in \{0, ..., T\}$

Parameters

- L^R: (in unit per period) regular production limits
- L^O: (in unit per period) overtime production limits
- M^{RP}: (in units per period) minimum regular production
- I^M_{-1}: (in unit) inventory of materials at the end of time -1
- I^P_{-1}: (in unit) inventory of products at the end of time -1
- H^M: (in unit) inventory capacity for materials
- H^P: (in unit) inventory capacity for products
- C^R: (in dollar per unit) regular production cost
- C^O: (in dollar per unit) overtime production cost

- C^{S}: (in dollar per unit) shortage cost
- C^{IM}: (in dollar per unit) inventory carrying cost of materials
- C^{IP}: (in dollar per unit) inventory carrying cost of products
- C^{FO}: (in dollar per order) fixed portion of the ordering cost for each order if an order is placed
- C^{VO}: (in dollar per unit) variable portion of the ordering cost
- B: (in unit) batch size
- T^{L}: (in time period) transportation lead time
- $\bar{O}$: (in batches) upper bound of orders

First stage decision variables (for time zero)

- x_0^R: (in unit) regular production in time zero
- x_0^O: (in unit) overtime production in time zero
- O_0: (in batch) material order placed in time zero
- I_0^M: (in unit) inventory of material at the end of time zero
- I_0^P: (in unit) inventory of product at the end of time zero
- S_0: (in unit) shortage of product in time zero
- y_0: whether (y_0 = 1) or not (y_0 = 0) an order is placed in time zero

Second stage decision variables (for times 1 to T)

- $x_{s,t}^R$: (in unit) regular production for time $t \in \{1, \dots, T\}$ under scenario $s \in \{1, \dots, S\}$
- $x_{s,t}^O$: (in unit) overtime production for time $t \in \{1, \dots, T\}$ under scenario $s \in \{1, \dots, S\}$
- $O_{s,t}$: (in batch) order of materials to be placed for time $t \in \{1, \dots, T\}$ under scenario $s \in \{1, \dots, S\}$

- $I_{s,t}^{M}$: (in unit) inventory of material at the end of time $t \in \{1, \dots, T\}$ under scenario $s \in \{1, \dots, S\}$
- $I_{s,t}^{P}$: (in unit) inventory of product at the end of time $t \in \{1, \dots, T\}$ under scenario $s \in \{1, \dots, S\}$
- $S_{s,t}$: (in unit) shortage of product for time $t \in \{1, \dots, T\}$ under scenario $s \in \{1, \dots, S\}$
- $y_{s,t}$: whether ($y_{s,t}$ = 1) or not ($y_{s,t}$ = 0) an order is placed for time $t \in \{1, \dots, T\}$ under scenario $s \in \{1, \dots, S\}$

Optimization Model

$$\min \quad C^R x_0^R + C^O x_0^O + C^{VO}.B.O_0 + C^{IM} I_0^M + C^{IP} I_0^P + C^S S_0 + C^{FO} y_0$$

$$+ \sum_{s=1}^{S} \sum_{t=1}^{T} p^s (C^R x_{s,t}^R + C^O x_{s.t}^O + C^{VO}.B.O_{s.t} + C^{IM} I_{s.t}^M \tag{1}$$

$$+ C^{IP} I_{s.t}^P + C^S S_{s.t} + C^{FO} y_{s.t})$$

s.t

$$I_0^M = I_{-1}^M + \Delta I_0 - (x_0^R + x_0^O) \tag{2}$$

$$I_{s,1}^M = I_0^M + \Delta I_1 - \left(x_{s,1}^R + x_{s,1}^O\right) \quad \forall s \in \{1, \dots, S\} \tag{3}$$

$$I_{s,t}^M = I_{s,t-1}^M + \Delta I_t - \left(x_{s,t}^R + x_{s,t}^O\right) \quad \forall s \in \{1, \dots, S\}, t \in \{2, \dots, T^L - 1\} \tag{4}$$

$$I_{s,T^L}^M = I_{s,T^L-1}^M + B.O_0 - \left(x_{s,T^L}^R + x_{s,T^L}^O\right) \quad \forall s \in \{1, \dots, S\} \tag{5}$$

$$I_{s,t}^M = I_{s,t-1}^M + B.O_{s,(t-T^L)} - \left(x_{s,t}^R + x_{s,t}^O\right) \quad \forall s \in \{1, \dots, S\}, \quad t \in \{T^L + 1, \dots, T\} \tag{6}$$

$$I_0^P = I_{-1}^P + (x_0^R + x_0^O) + S_0 - d_0 \tag{7}$$

$$I_{s,1}^P = I_0^P + \left(x_{s,1}^R + x_{s,1}^O\right) + S_{s,1} - D_{s,1}^{\alpha} \quad \forall s \in \{1, \dots, S\} \tag{8}$$

$$I_{s,t}^P = I_{s,t-1}^P + \left(x_{s,t}^R + x_{s,t}^O\right) + S_{s,t} - D_{s,t}^{\alpha} \quad \forall s \in \{1, \dots, S\}, t \in \{2, \dots, \mathrm{T}\} \tag{9}$$

$$D_{s,t}^{\alpha} = d_t + \alpha.R_{s,t}^{\alpha} \quad \forall s \in \{1, \dots, S\}, t \in \{1, \dots, \mathrm{T}\} \tag{10}$$

$$O_0 \leq \bar{O} y_0 \tag{11}$$

$$O_{s,t} \leq \bar{O} y_{s,t} \;\; \forall s \in \{1, \ldots, S\}, t \in \{1, \ldots, \mathrm{T} - T^L\} \tag{12}$$

$$M^{RP} \leq x_0^R, x_{s,t}^R \leq L^R \;\; \boldsymbol{integer} \;\; \forall s \in \{1, \ldots, S\}, t \in \{1, \ldots, \mathrm{T}\} \tag{13}$$

$$0 \leq x_0^O, x_{s,t}^O \leq L^O \;\; \boldsymbol{integer} \;\; \forall s \in \{1, \ldots, S\}, t \in \{1, \ldots, \mathrm{T}\} \tag{14}$$

$$0 \leq I_0^M, I_{s,t}^M \leq H^M \;\; \boldsymbol{integer} \;\; \forall s \in \{1, \ldots, S\}, t \in \{1, \ldots, \mathrm{T}\} \tag{15}$$

$$0 \leq I_0^P, I_{s,t}^P \leq H^P \;\; \boldsymbol{integer} \;\; \forall s \in \{1, \ldots, S\}, t \in \{1, \ldots, \mathrm{T}\} \tag{16}$$

$$S_0, S_{s,t}, O_0, O_{s,t} \geq 0 \;\; \boldsymbol{integer} \;\; \forall s \in \{1, \ldots, S\}, t \in \{1, \ldots, \mathrm{T}\} \tag{17}$$

$$y_0, y_{s,t} \geq 0 \;\; \boldsymbol{binary} \;\; \forall s \in \{1, \ldots, S\}, t \in \{1, \ldots, \mathrm{T}\} \tag{18}$$

The objective function in equation (1) has two parts. The first part is the total cost of production for the current period which has a subscript of zero. The second part which is a summation of costs in various scenarios weighted by their probabilities. Equations (2) - (6) are related to the raw material inventory. The basic idea of these equations is that the raw material inventory at the end of a period is equal to the sum of inventory at the end of the previous period and the incoming inventory in the present period minus the total production in the present period. The equations (7) - (9) are related to the finished product inventory. Similar to the raw material inventory equations, the idea for these equations is that the finished product inventory at the end of the present period is equal to the sum of the finished product at the end of the previous period, the total production in the present period and the shortage in the present period minus the demand that is satisfied in the present period.

In equation (10) α varies from 0 to 10000 in increments of 1000 thus allowing us to study the behaviour of the model with varying error magnitude in the forecast of the demand by the manufacturer. Equations (11) and (12) establish a link between the binary variable (y) and the order (O). This ensures that the binary variable is one only when an order is placed otherwise it is zero. The remaining equations from (13) to (18) are limits on the variables and non-negativity constraints.

Case study

To understand the behaviour of our model on actual monthly demand data we have considered three demand data sets. They are vehicle sales (1967-2017), books and sporting goods (2006-2018) and bulk sales of milk (1999-2018) which was taken from https://fred.stlouisfed.org. This is taken as an input for the case study and we try to make decisions related to production and inventory control for manufacturer and the supplier using various optimization strategies. The trend line which is a six-degree polynomial curve fit on the figures below show the extent of variation in demand. If the lines have more amplitude, it indicates more swings in the trend. If there is a smooth transition in demand data, it means he extent of variation is less.

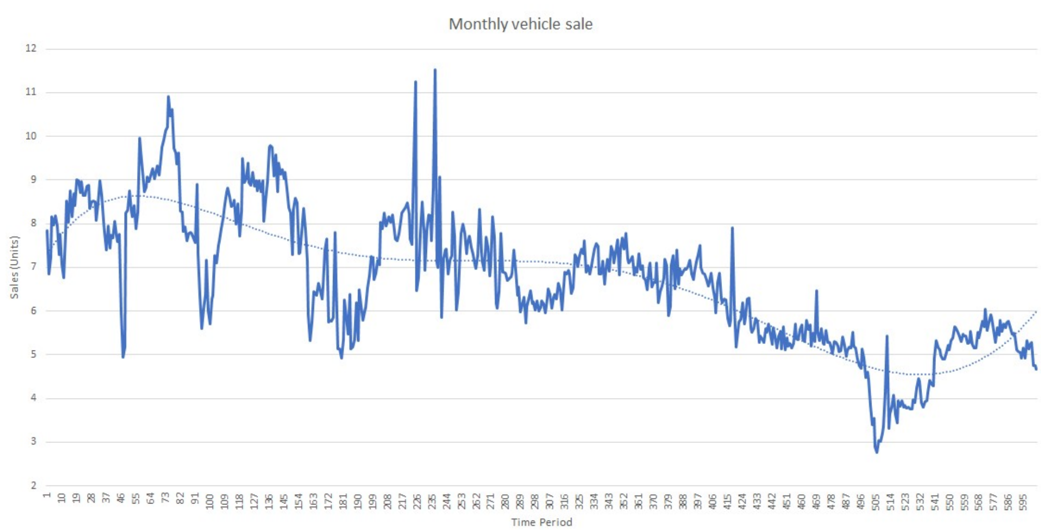

Figure 3 Trend in monthly vehicle sales (Federal Reserve Bank of St. Louis, 2018c)

Figure 4 Trend in monthly book sales (Federal Reserve Bank of St. Louis, 2018b)

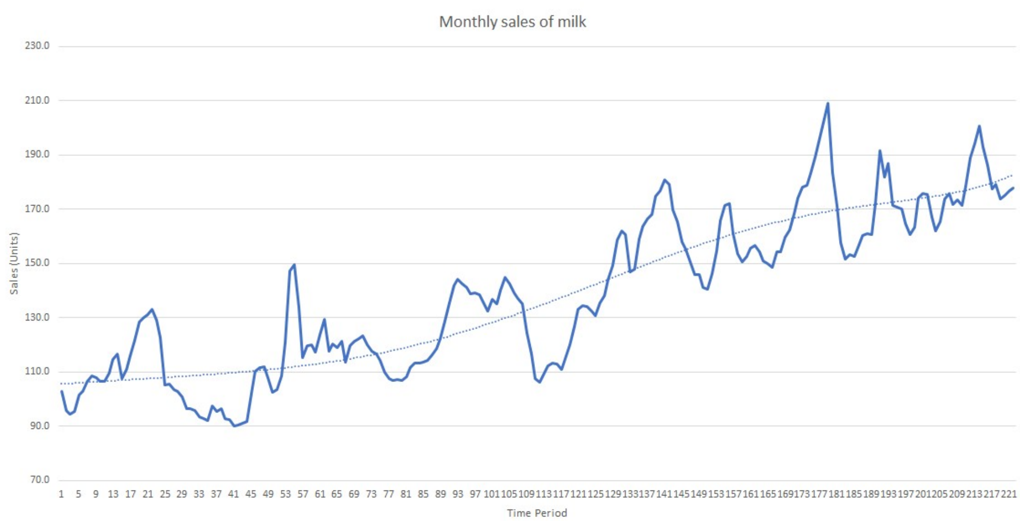

Figure 5 Trend in monthly milk sales (Federal Reserve Bank of St. Louis, 2018a)

As discussed earlier, there are two optimization strategies that can be used by the manufacturer or the supplier. We are going to denote deterministic strategy as *D* and stochastic strategy as *S*. There can be different combinations of the strategies depending on number of participants in a supply chain. In our study, as we are considering two participants, there can be four possible combinations. We look at these possible combinations of optimization strategies for making production and inventory management decisions between a manufacturer and a supplier and try to understand which is better for them. To identify and analyse the results, for our convenience, we have coded the strategies and their combinations as shown in the table below.

Table 1 Combination of strategies

Scenario	**Manufacturer**	**Supplier**
DD	Deterministic	Deterministic
DS	Deterministic	Stochastic
SD	Stochastic	Deterministic
SS	Stochastic	Stochastic

The manufacturer's demand forecast varies with the magnitude of error α. However, the supplier uses their own data from the past to make the forecast and use it as the demand data in the optimization models as described earlier. Figure 6 shows the rolling horizon concept (Rahdar et al., 2018). In this figure *P(t)* is the solution of the decision-making model for time t which includes the red and the blue portion. The red portion is the decision variables for the current period and the blue portion is for the future. Though the number of demand data points available in each data set is different in each period, the planning horizon remains the same. This simulation is for each strategy combination and is repeated with different demand data forecasting accuracy from zero to ten thousand. Hence, for each data set, there are forty-four simulations. Furthermore, as we also consider information sharing, this number would be eighty-eight total simulations. The parameters for the simulation are shown in Table 2.

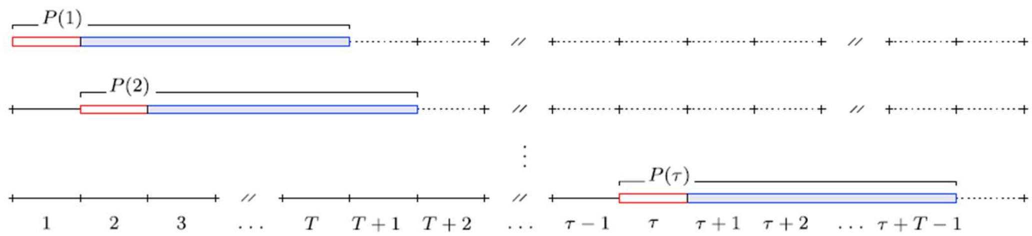

Figure 6 Rolling horizon approach (Rahdar et al., 2018)

For the case study the input parameters are as given in Table 2. The code was written in MATLAB using CPLEX solver interface on an HP laptop with Intel-i5-5200U processor @2.20 GHz and 8.00 GB RAM. The operating system was 64-bit Windows 10.

Table 2 Simulation parameters

Parameters	Manufacturer	Supplier
Regular Production Limit (L^R)	120,000	140,000
Overtime Production Limit (L^O)	80,000	80,000
Minimum Regular Production (M^{RP})	20,000	20,000
Material Inventory (I_{-1}^M)	60,000	50,000
Product Inventory (I_{-1}^P)	50,000	40,000
Material Inventory Capacity (H^M)	300,000	300,000
Product Inventory Capacity (H^P)	300,000	300,000
Regular Production Cost (C^R)	20	5
Overtime Production Cost (C^O)	30	10
Shortage Cost (C^S)	100	50
Material Inventory Carrying Cost (C^{IM})	0.5	0.4
Product Inventory Carrying Cost (C^{IP})	0.5	0.4
Fixed Ordering Cost (C^{FO})	100	60
Variable Ordering Cost (C^{VO})	30	10
Order Batch Size (B)	100	100
Transportation Lead Time (T^L)	2	2
Upper Bound on Orders ($\bar{O}$)	10,000	10,000

CHAPTER 4. RESULTS

In this section, effect of optimization strategies on bull-whip effect and total mean operational cost will be discussed. Effect of Information sharing is also studied to know if it is always beneficial in saving costs and reducing the bull-whip effect. In the following Figures, scenario code has been used to indicate the strategy used by the manufacturer and the supplier as shown in Table 1.

Effect of optimization strategies

Propagation of demand data, total mean operating cost and bull-whip effect are evaluated for each possible combination of strategy. These parameters are plotted against the root mean squared error values for various magnitudes of errors in demand data forecast to compare the performance of the strategy combinations.

Propagation of demand in a supply chain

Demand uncertainty is a challenge that a manufacturer needs to tackle in the best possible way to reduce the costs. Optimization techniques can help in making better decisions under uncertain demand. The variation in the orders placed by the manufacturer is the demand for the supplier. This is plotted against the corresponding RMSE values for all the possible strategies.

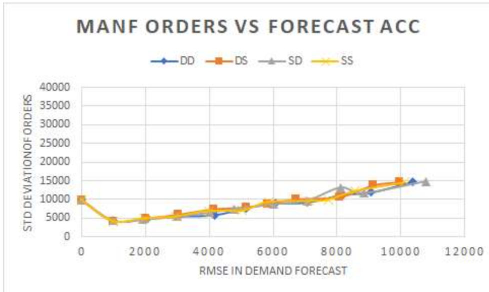

Figure 7 Manufacturer orders in book sales

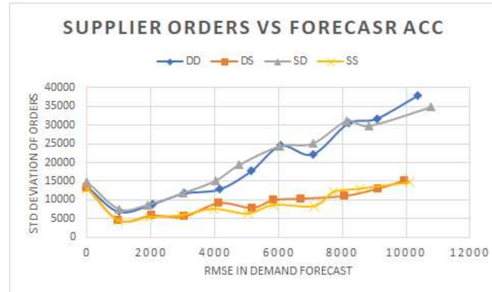

Figure 8 Supplier orders in book sales

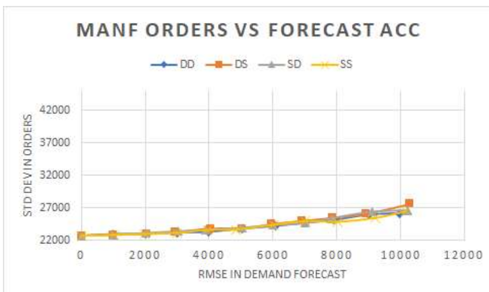

Figure 9 Manufacturer orders in vehicle sales

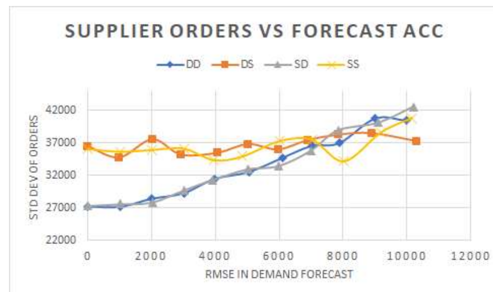

Figure 10 Supplier orders in vehicle sales

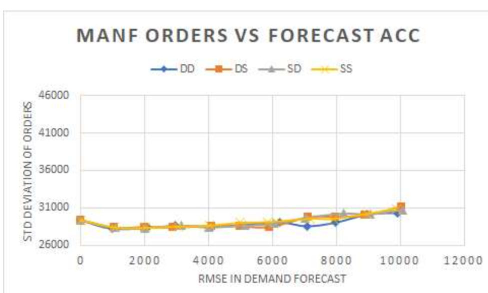

Figure 11 Manufacturer orders in milk sales

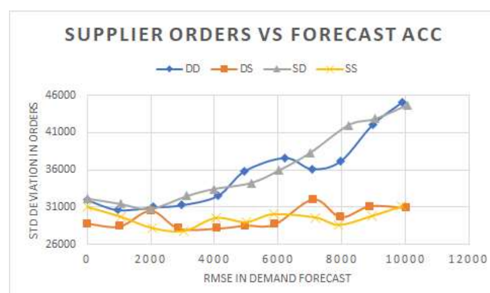

Figure 12 Supplier orders in milk sales

It can be seen in the figures above that the choice of optimization strategy of the supplier does not affect his demand variation. In most cases, the variation in the demand of the supplier increased with increase in the RMSE in demand forecast of the manufacturer Irrespective of the strategy chosen by the manufacturer, the variation in the order of raw material placed by the supplier remains constant when the supplier uses stochastic strategy.

On the other hand, when the supplier uses deterministic strategy, the variation in raw material orders placed by the supplier increases with increase in RMSE in demand forecast of the manufacturer. It can also be seen that the variation in the orders placed by the supplier is more when compared to that of the manufacturer. Also, this increase is more when the forecast error is more.

Total mean operational cost

This section looks at the variation in the total mean cost of operation incurred by the manufacturer and the supplier in all the four possible combination of strategies. Again, the variation is studied with respect to the RMSE in demand forecast.

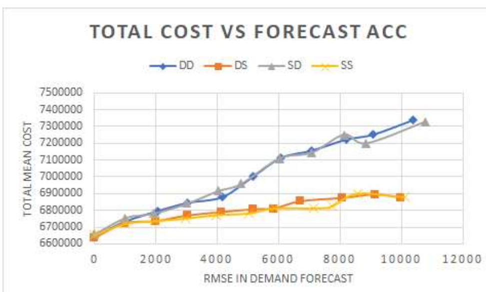

Figure 13 Total mean operational cost in book sales

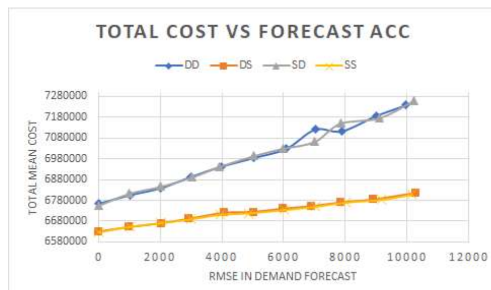

Figure 14 Total mean operational cost in vehicle sales

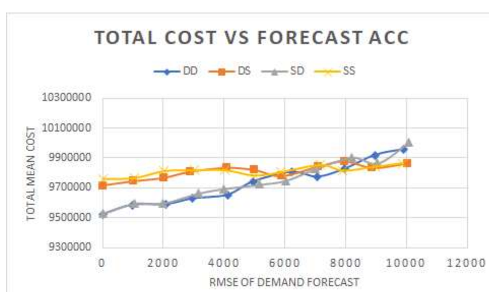

Figure 15 Total mean operational cost in milk sales

The total mean cost of operation remains constant with increasing RMSE in demand forecast when the supplier uses stochastic optimization strategy. Furthermore, it increases with RMSE when the supplier uses deterministic strategy. Hence, the total mean cost of operation mostly depends on the choice of strategy by the supplier. However, the best strategy for the supplier would depend on the type of demand data. If the trend in the variation of demand data of the manufacturer follows a smooth curve, it is better if both the stake holders use deterministic strategy. If the variation in the trend of the manufacturer's demand is not smooth, it is beneficial for both the stake holders to use stochastic strategy.

Bull-whip effect

The bull-whip effect is the increase in the variation of orders placed along the upstream supply chain. This increase or decrease in variation of orders was captured by calculating the standard deviation of the orders placed at each stage in the two-echelon supply chain. In the following figures, the difference in the standard deviation of the orders placed by the supplier and the manufacturer is plotted for all the possible strategy combinations against the RMSE in demand forecast of the manufacturer.

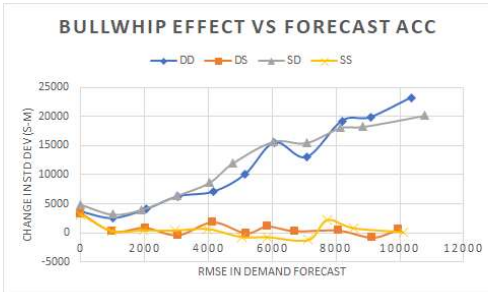

Figure 16 Bull-whip effect in book sales

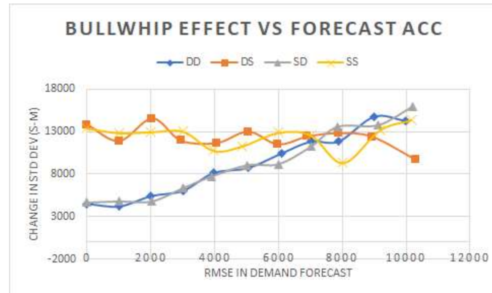

Figure 17 Bull-whip effect in vehicle sales

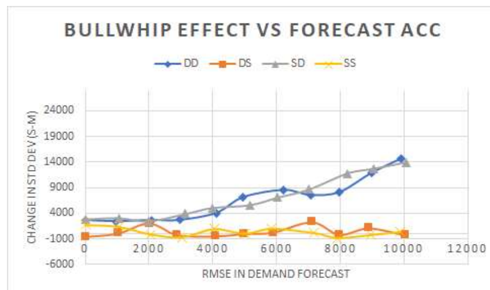

Figure 18 Bull-whip effect in milk sales

When the supplier uses stochastic strategy, irrespective of the strategy used by the manufacturer, the bull-whip effect decreases with increase in the RMSE in demand forecast of the manufacturer. While the situation is completely opposite when the supplier uses deterministic strategy.

Information sharing

The information sharing considered in this research is limited to the possible future orders predicted by the optimization strategy in each period. The effect of information sharing on total mean operational cost and the bull-whip effect is evaluated in this section. The effect of information sharing on the cost is measured by calculating the savings and plotting it against the RMSE in manufacturer's demand forecast.

Operational cost saving

There is cost saving when information on possible future orders is shared.

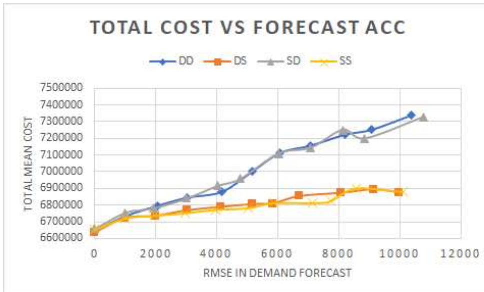

Figure 19 Total mean operational cost in book sales – No information sharing

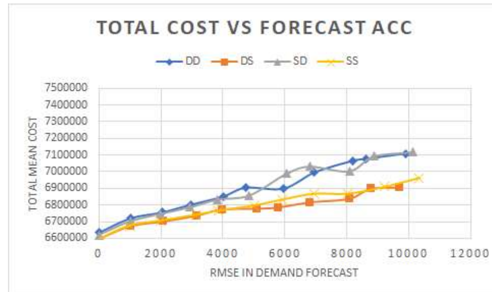

Figure 20 Total mean operational cost in book sales – Information sharing

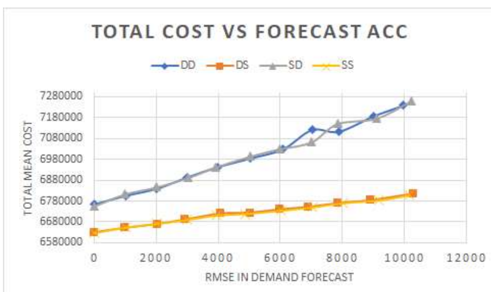

Figure 21 Total mean operational cost in vehicle sales – No information sharing

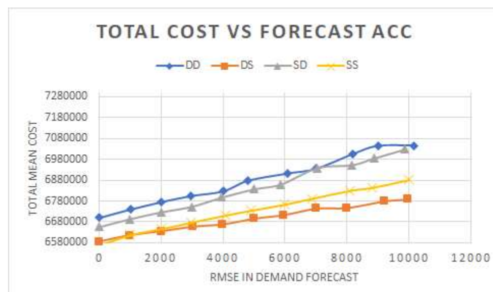

Figure 22 Total mean operational cost in vehicle sales – Information sharing

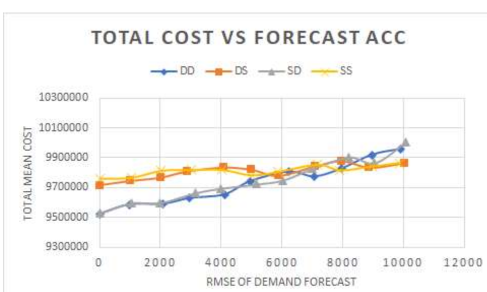

Figure 23 Total mean operational cost in milk sales – No information sharing

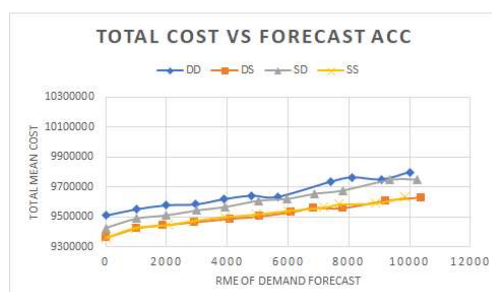

Figure 24 Total mean operational cost in milk sales – Information sharing

In the figures shown above, the graphs of the total mean operational cost with and without information sharing for all the three demand data sets is compared. The costs are plotted against the RMSE in the demand forecast of the manufacturer. The cost saving in situations where supplier uses stochastic strategy, either remains stable or decreases with increase in RMSE. On the other hand, when supplier uses deterministic strategy, the cost saving either remains stable or increases with increase in RMSE.

Bull-whip effect reduction

In this section, the variation in bull-whip effect with respect to RMSE for all the three demand data sets, with and without information sharing has been compared. Information sharing results in a smooth bull-whip effect curve. However, as seen in the figures below, the trend is unaffected by information sharing. There is a decrease in bull-whip effect after information sharing only when the manufacturer uses deterministic strategy in most cases.

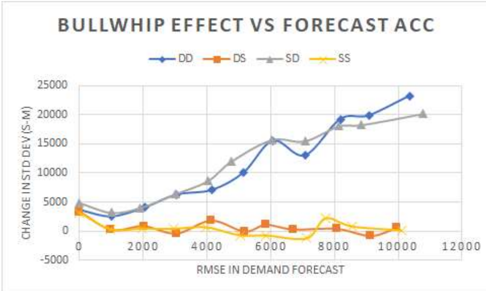

Figure 25 Bull-whip effect in book sales – No information sharing

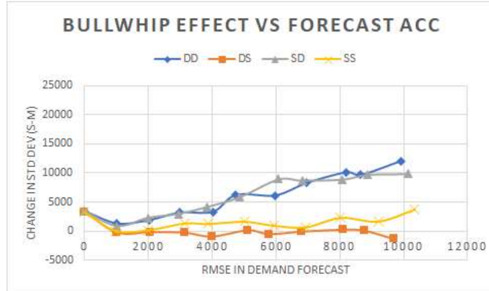

Figure 26 Bull-whip effect in book sales – Information sharing

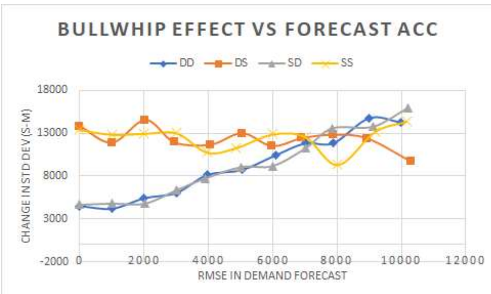

Figure 27 Bull-whip effect in vehicle sales – No information sharing

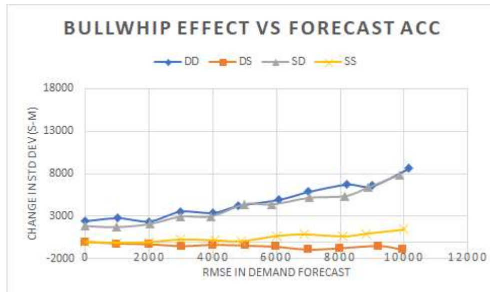

Figure 28 Bull-whip effect in vehicle sales – Information sharing

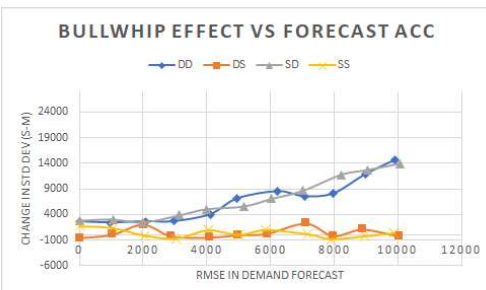

Figure 29 Bull-whip effect in milk sales – No information sharing

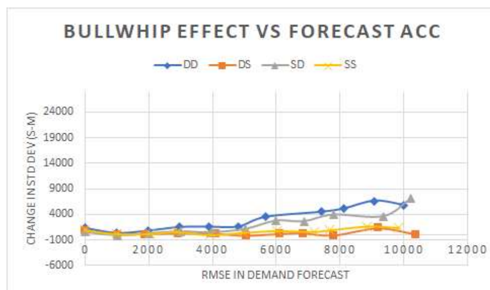

Figure 30 Bull-whip effect in milk sales – Information sharing

CHAPTER 5. CONCLUSIONS

The aim of this research is to understand how deterministic and stochastic optimization models effect the operational costs and the bull-whip effect in a two-echelon supply chain. In the deterministic optimization model one scenario of demand is assumed a repeat pattern forecasting is used. While in the stochastic strategy, six scenarios are randomly chosen from the past and are weighted with assumed probabilities. Highest probability is assigned to the latest scenario. The oldest scenario gets the least probability. This is true only for the supplier. The manufacturer does not rely on the past demand data for forecast. His demand data forecast is controlled by error magnitude. All the four possible combinations of strategies were studied with and without information sharing. Bull-whip effect, propagation of demand and the total mean operational cost is observed when the manufacturer and the supplier used different optimization models with respect to change in the RMSE in demand forecast of the manufacturer.

It is found that the total operational cost is driven by the choice of strategy of the supplier. It is the least when the supplier uses stochastic optimization strategy irrespective of the strategy used by the manufacturer. However, it is beneficial to use deterministic strategy when the trend line of variation in demand is smooth. With regards to the propagation of demand along the supply chain, it is observed that the choice of optimization strategy by the supplier does not affect his demand. On the other hand, in most cases, when the supplier uses deterministic strategy, orders of raw material placed by the supplier increases with increase in RMSE of demand forecast of the manufacturer.

Trend in the bull-whip effect is driven by the choice of strategy of the supplier. Bull-whip effect decreases in most cases when the supplier uses use stochastic strategy. However, it also remains constant in some cases. When the supplier uses deterministic strategy, the bull-whip effect increases with increase in RMSE of demand forecast.

Information sharing results in operational cost saving in almost all the combination of strategies except for few instances where the RMSE in demand data forecast is high. The cost savings decreases with increase in RMSE when the supplier uses stochastic strategy. It is the opposite when deterministic strategy is used by the supplier.

This research helps in understanding the interaction of the strategies in a supply chain. It also provides an approach to study the supply chain performance in terms of operational costs and bull-whip effect with different types of demand data. The result of including multiple stakeholders in the supply chain and the use of different set of parameters can be considered in the future.

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APPENDIX SHORTAGE

The variation in total shortage of units is shown in the graphs below. It is seen that there is a decrease in shortage when information regarding the future orders is shared.

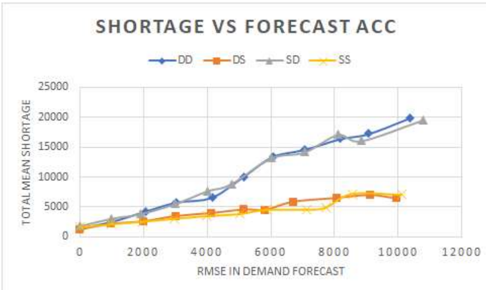

Figure 31 Shortage in book sales – No information sharing

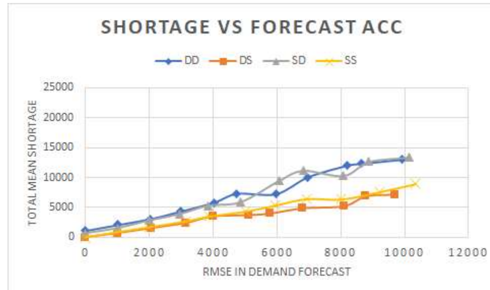

Figure 32 Shortage in book sales - Information sharing

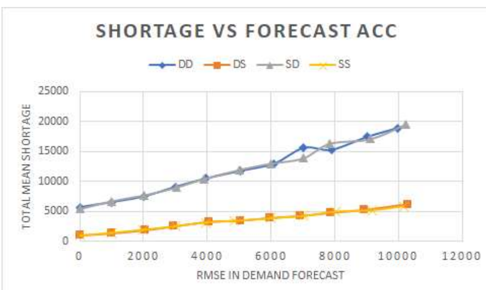

Figure 33 Shortage in vehicle sales – No information sharing

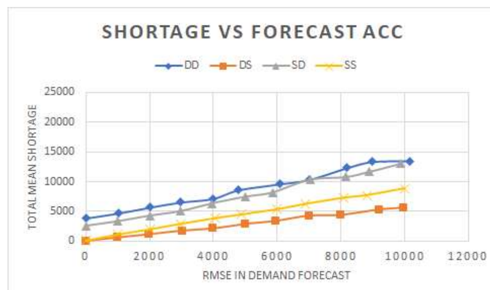

Figure 34 Shortage in vehicle sales – Information sharing

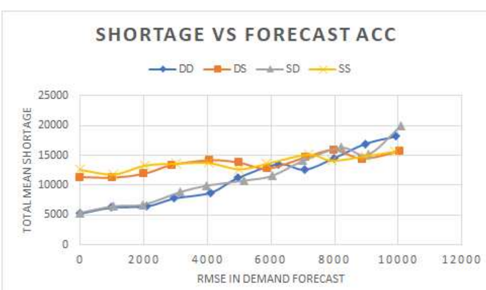

Figure 35 Shortage in milk sales – No information sharing

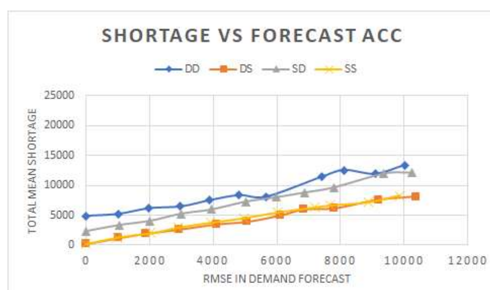

Figure 36 Shortage in milk sales – Information sharing