Supply Strategy with System Dynamics

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Author's Foreword

To manage your supply chain well, you need to understand the principles of the supply chain. It is designed to flow materials, information, etc., and must be drilled quickly when blocked. But supply chains are complex. With so many stakeholders involved and acting for their own interests, conflicts inevitably occur. For now, for whom? What to manage? And what will you do to achieve your desired goal? Although it is very important, it is impossible to even detect it due to the complexity of the system.

This book offers a more systematic way to analyze supply chains that have hitherto been covered up as complex. A good understanding of how it works will make supply chain management smoother. And it presents various supply chain strategies. Knowing and responding to how hypothetical strategic actions will affect the supply chain can lead to more effective policy formulation. This is also the reason for conducting simulations.

In this book, the three-step model is taken as a basis. It was named Model 357. The two-stage model is relatively simple, so it seems that the characteristics of the supply chain cannot be captured well, and if it reaches the fourth stage or more, it will be too complicated to understand, so it is set to the third stage.

Based on the basic model, we will first look at how the supply chain changes in response to changes in demand. How to set up the safety stock is covered. Next, we look at changes in lead times that have a lot of impact on supply chain performance. Simulations show that changes in lead times downstream are more important than changes upstream.

Words alone cannot say that information sharing is important. The extent to which information sharing affects supply chain inventory and inventory fulfillment rates is quantitatively shown in Chapter 4. Chapter 5 examines how heuristics present in human decision-making negatively affect supply chains. In particular, it suggests that demand-following heuristics are heuristics that must be avoided in the supply chain.

Chapter 6 shows the sectoral and global optimization processes and examines how big the differences between them are. Chapter 7 then deals with the effects of supply contracts and decoupling strategies for global optimization. Supply contracts or decoupling strategies are strategies that should be utilized in the design of desirable supply chains in the future.

Chapter 8 deals with a rather unusual phenomenon. Instead of following the basic model, a new model of 1-2 was created to depict a shortfall game in the supply chain. We then analyzed the effects of information sharing.

Chapter 9 focuses on the transportation part, which accounts for the vast majority of logistics costs. It is a model in which the availability of transport trucks and the supply chain management module are connected to interact with the two flows. Although it is relatively complex, the model has been completed to a level that can be applied in real life. When optimizing the supply chain, the volume of transport trucks is also taken into account.

1 Chapter0 deals with emergency channels, a form of supply chain strategy. Having an emergency channel has the disadvantage of increasing complexity, but it was introduced as a strategic alternative that increases resilience and efficiency at the same time. Chapter 11 introduces the most challenging of all pooling . Lead time pooling was implemented as a factor that could make the three-stage supply chain more efficient than the two-stage supply chain . One factor that must be considered when designing a supply chain is lead time pooling.

1 Chapter2 connects product strategy and supply chains. Among various product strategies, it implements the product life cycle that considers the word of mouth effect and advertising effect, and suggests important points in supply chain management accordingly. Furthermore, Chapter 13 suggests through optimization methods when it is most efficient to stop buying when a product is out of date. 1 When a product is about to stop selling at the end of October, the simulation shows when it will be most profitable to stop production or purchase. The final chapter , capacity management, shows how performance varies depending on the size of the chunk and the general strategy of capacity management. In particular, delays in decision-making inevitably lead to significant inefficiencies.

As described above, most chapters commonly use a three-step inventory management model. In addition, the simulation model was modified by changing strategies and management points. Therefore, we recommend that you read this book slowly from chapter 1. In the back, the model presented earlier was omitted as much as possible to avoid duplication. And if you want to become an expert in supply chain management, you can install the Vensim program and read it while running the program one by one, and you will have the pleasure of improving your understanding and skills .

contents

Chapter 1

Three-step supply chain model

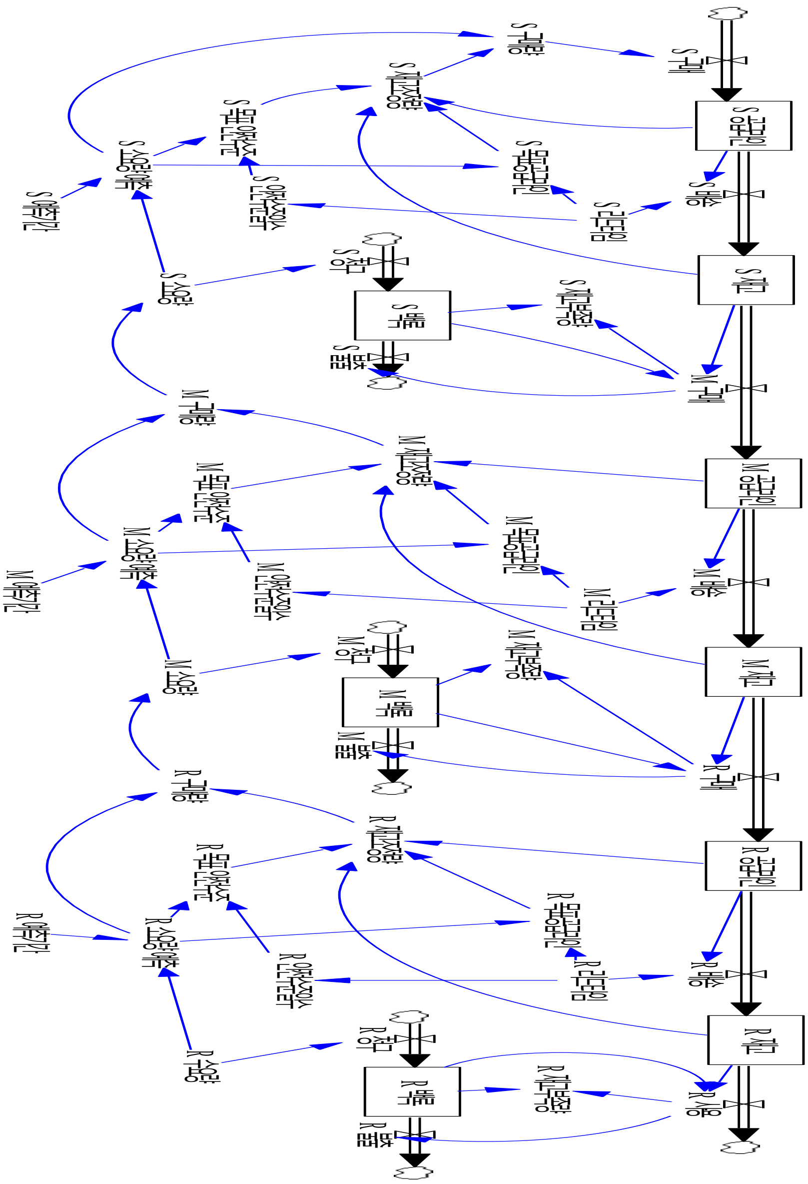
A 3-echelon Supply Chain as a Base Model

1) Basic supply chain model in three phases

If we expand the basic inventory model covered in Inventory Management Using System Dynamics (BookCube, 2022), we can create the following three-step inventory model. Three-stage supply chains are common. If it leads to supplier-producer-distributor or logistics-governor-division, it is a three-stage supply chain. Here, it is named S-M-R.

The reason for starting the supply chain from step 3 is that stage 2 is too simple, and step 4 is very complicated. There are phenomena that occur at least three levels in the supply chain. One example is the Bullwhip Effect. It is a phenomenon in which order information is amplified as it goes upstream. We'll see more about this reason, but fundamentally it's a delay, a decision heuristic.

<Figure 1-1> Phase 3 Supply Chain



The formula used in the model is shown in Table 1-1> < below.

<Table 1-1> Formula of Phase 3 Supply Chain

M Supply Line = INTEG (M Purchase-M Delivery, M Target Supply Line)
M Purchase=MIN(S Backgreen, S Stock)
M Purchase Volume = M AX (0, M Consumption Forecast + M Inventory Adjustment)
M lead time=5
M target safety level = M required quantity prediction*M safety level days

M Target Supply Line = M Prediction of Requirements* M Lead Time
M Shipping=M Supply Line/M Lead Time
M backrock= INTEG (M claim-M non-yield,100)
M withdrawn=R purchase
M Requirement Prediction = SMOOTH (M Requirement, M Prediction Period)
M Requirement = R Purchase Volume
M Safety Level Days=M Lead Time
M Forecast period=3
M Inventory = INTEG (M Shipping-R Purchase, M Target Safety Level)
M Stockout=MAX(0, M Backrock-R Purchase)
M Inventory Adjustment Amount= M Target Supply Line-M Supply Line+M Target Safety Level-M Inventory
M Charge=M Requirement
R Supply Line = INTEG (R Purchase-R Delivery, R Target Supply Line)
R BUY= MIN(M Stock, M Backrock)
R purchase volume = MAX (0, R requirement forecast + R inventory adjustment)
R lead time=3
R target safety level = R required prediction * R safety level days
R Target Supply Line = R Prediction of Requirements*R Lead Time
R Shipping= R Supply Line/R Lead Time
R backrock= INTEG (R claim-R dismissed,100)
R dismissed= Use R
Use R= MIN(R backrock, R stock)
R Requirement Prediction = SMOOTH (R Demand, R Forecast Period)
R Demand=100+STEP(100, 101)
R Safety Level Days = R Lead Time
R prediction period=3
R Inventory = INTEG (R Shipping-R Enabled, R Target Safety Level)
R Outstock=MAX(0, using R backrock-R)
R Inventory Adjustment Amount=R Target Safety Level-R Inventory+R Target Supply Line-R Supply Line
R Charge= R Demand
S supply line = INTEG (S purchase-S delivery, S target supply line)
S purchase = S purchase volume
S purchase volume = MAX (0, S inventory adjustment + S requirement forecast)
S lead time=7
S target safety level = S Prediction of required volume*S number of days of safety level
S Target Supply Line = S Forecast Requirement*S Lead Time
S Shipping=S Supply Line/S Lead Time

S backrock = INTEG (S claim-S non-yield,100)
S dismissed= M purchase
S requirement prediction = SMOOTH (S requirement, S prediction period)
S Requirement=M Purchase Volume
S Safety Level Days = S Lead Time
S Prediction period=3
S Inventory = INTEG (S Shipping-M Purchase, S Target Safety Level)
S Out-of-stock = MAX(0, S backrock-M purchase)
S Inventory adjustment amount = S target safety level-S inventory+S target supply line-S supply line
S Claim= S Requirement

FINAL TIME = 365 Day
INITIAL TIME = 0 Day
TIME STEP = 1 Day

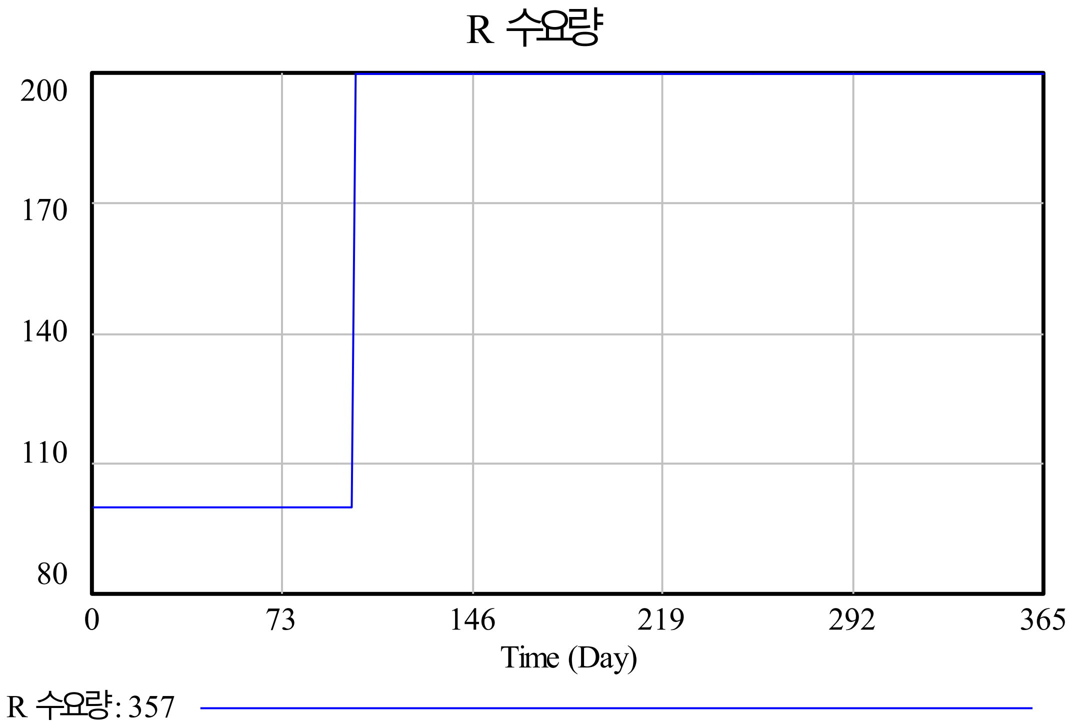
In the case of R demand, which can be called an exogenous variable, it was set to 100 from 0 to 100 days, and 200 from 101 to 365 days. To see what it looks like when there's one shock in the supply chain. The simulation period is from 0 to 365 days, for a total of 366 days, and the time step is 1 day. Actions are performed on a one-day basis.

Various parameters were used in this model, especially in the supply chain, such as lead times, target safety levels, and target supply lines. When the stock value of the system is adjusted by the negative loop, the reference values are the target stock level and the target supply line. In this model, two types of stocks are managed: inventory and supply lines.

For simplicity, R's lead time, target supply line, and target inventory level were all applied to 3 days. 5 days were applied for M and 7 days for S. From R's point of view, inventory has 3 days (3 days times forecast demand), and the supply line also has 3 days. S has 7 days of inventory and supply lines. This is because in general, downstream orders (billing) and deliveries are made more frequently in the supply chain than upstream. Depending on the supply chain, all of these parameters can be modified. <Figure 1-1> models have not yet reflected uncertainty in demand or uncertainty in lead times.

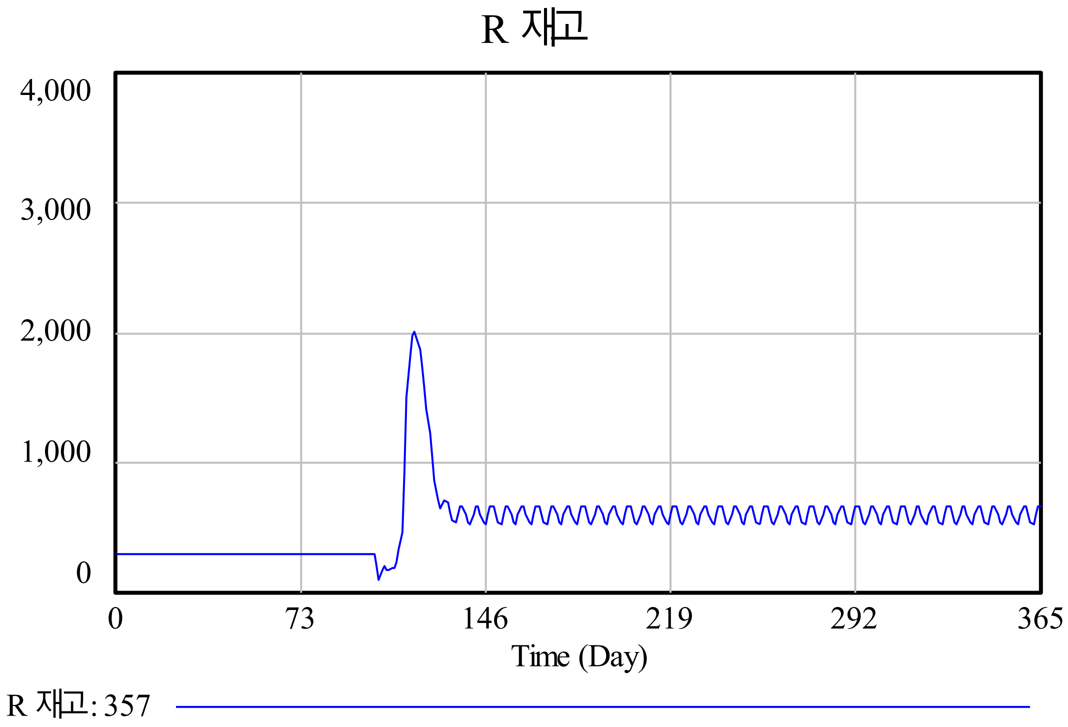
The demand forecast periods of the three members of the supply chain (R, M, S) were all applied as lead times. R applied the SMOOTH function of 3 periods, M applied 5 periods, and S applied 7 periods.

<Figure 1-2> R demand over time



The formula of 100 + STEP (100, 101) was used to generate stepped demand. There will be 100 demands until the 100th, and 200 demands from the 101st. Accordingly, the change in R inventory is shown in the following figure.

<Figure 1-3> Changes in R Inventory

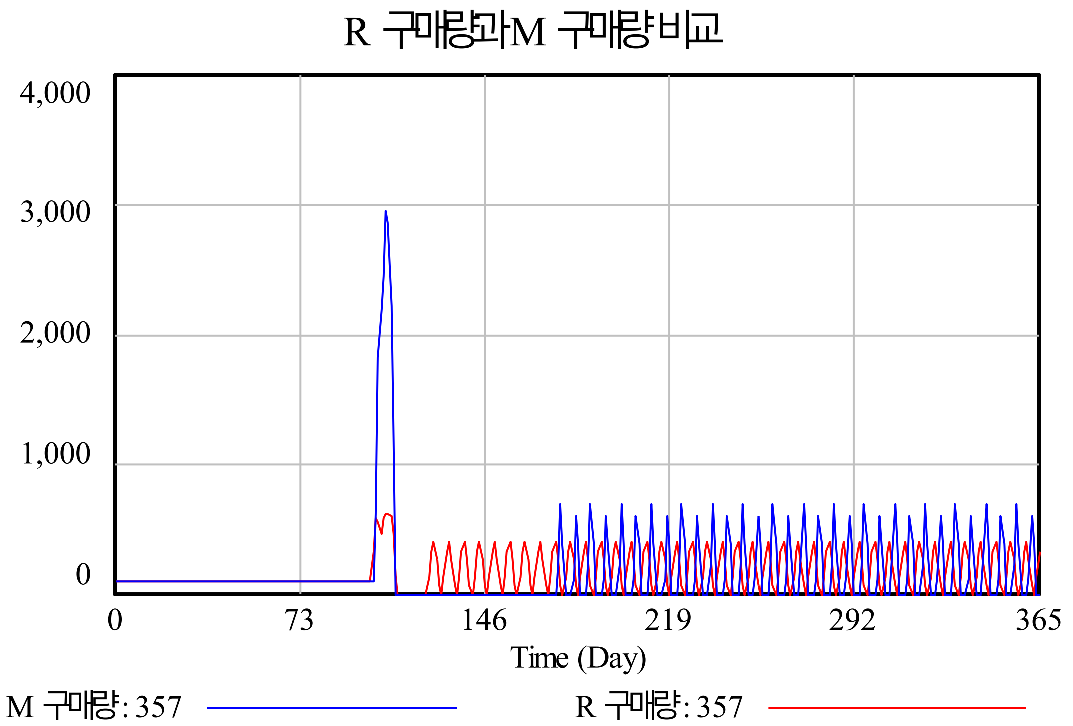


<R inventory below Figure 1-3>: The number in 357 is the vensim datafile name. The target stock of R inventory is 3 days. Between 0 and 100 days, it remains at 300. There is a shock on the 101st, when the inventory falls below the target stock level and then recovers again. It has increased to 2,000 and is then balanced again at around 600. In this way, depending on the impact, the amount of inventory is above the target stock, and this upward convex part is called an overshoot (overshoot). It must happen because there is a delay of 3 days. Around 130 days, the inventory shows oscillation. This also occurs due to lead times. Why is the lead time the same for the first 100 days, but not initially absent and then happens later? You have to ask the obvious questions. Initially, the inventory adjustment value is 0, and then the inventory adjustment value occurs positively. However, this is because there is a time gap between the value you want to adjust and the actual entry into the inventory, so the adjustment is not perfect. When oscillation occurs within a certain range, system dynamics scholars believe that coordination is being made well. Equilibrium is considered to be achieved. If the oscillation is widened, I don't think it is balanced.

Another thing to note is that R's inventory is too large for the amount below the target level. This includes the impact of lead times of M and S. There is a shortage of stock, because M is also out of stock and cannot provide properly. We'll analyze this a little later.

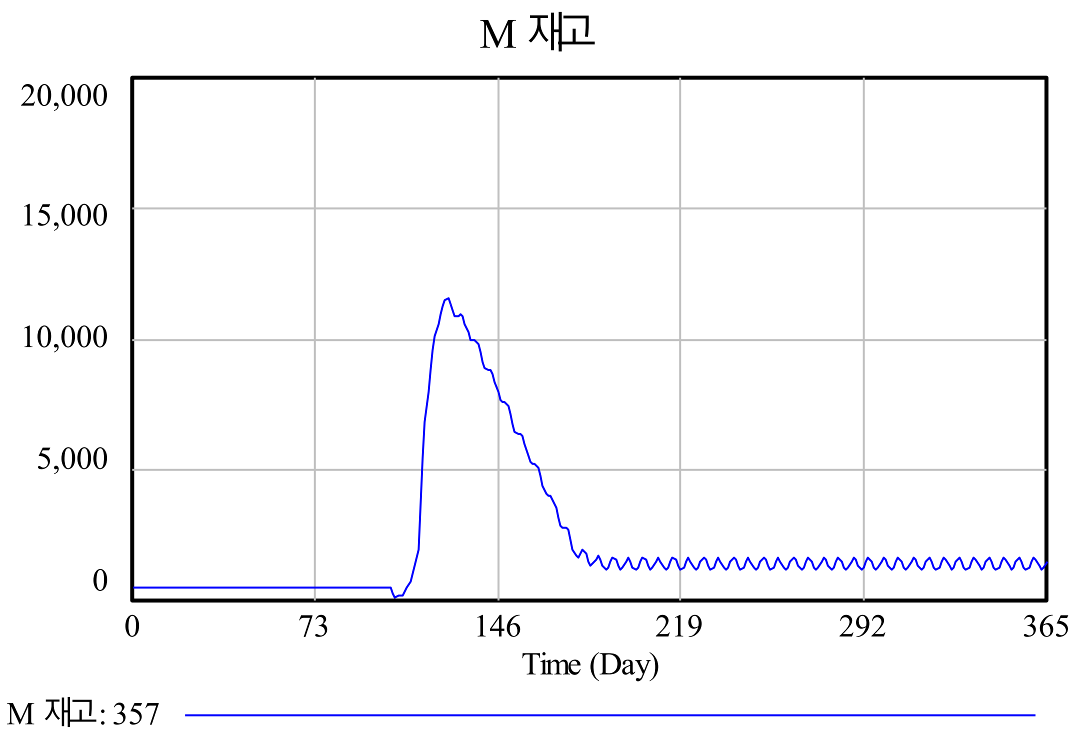
M performs the same management as R. Only the lead time was changed from 3 days to 5 days. Of course, the difference is that the number of demands accepted by M is the purchase volume of R. First, let's look at the purchase volume of M.

<Figure 1-4> Changes in R and M purchases



After the shock on day 101, the purchase volume pattern of M and R is similar. The difference is that the amplification of the purchase volume of M occurs more significantly, and the period in which the purchase amount is zero occurs longer. Accordingly, the M inventory is as follows. The demand for the end was 100 or 200, but the purchase volume of M is approaching 3,000 at a time. This is because M's lead time is long, and M wants to adjust the supply line and inventory at the same time. The act of ignoring the supply line is modeled so that it does not occur.

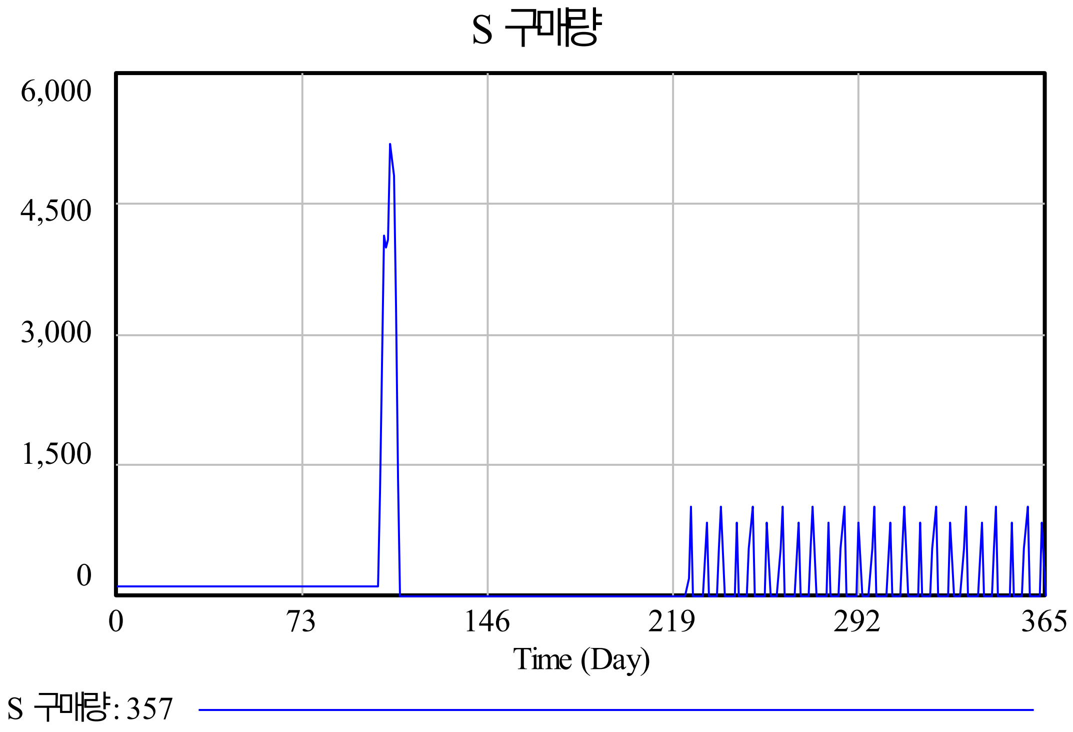
<Figure 1-5> M Inventory Change



Compared to R inventory, M inventory has a greater overshoot. The inventory exceeds 10,000 units and returns to equilibrium at the end of 200 days. The maximum value of R stock is about 2,000, but the maximum value of M stock exceeds 11,500. M should have a warehouse to store 11,500 pieces. For reference, the average of M stock is only 2,130.

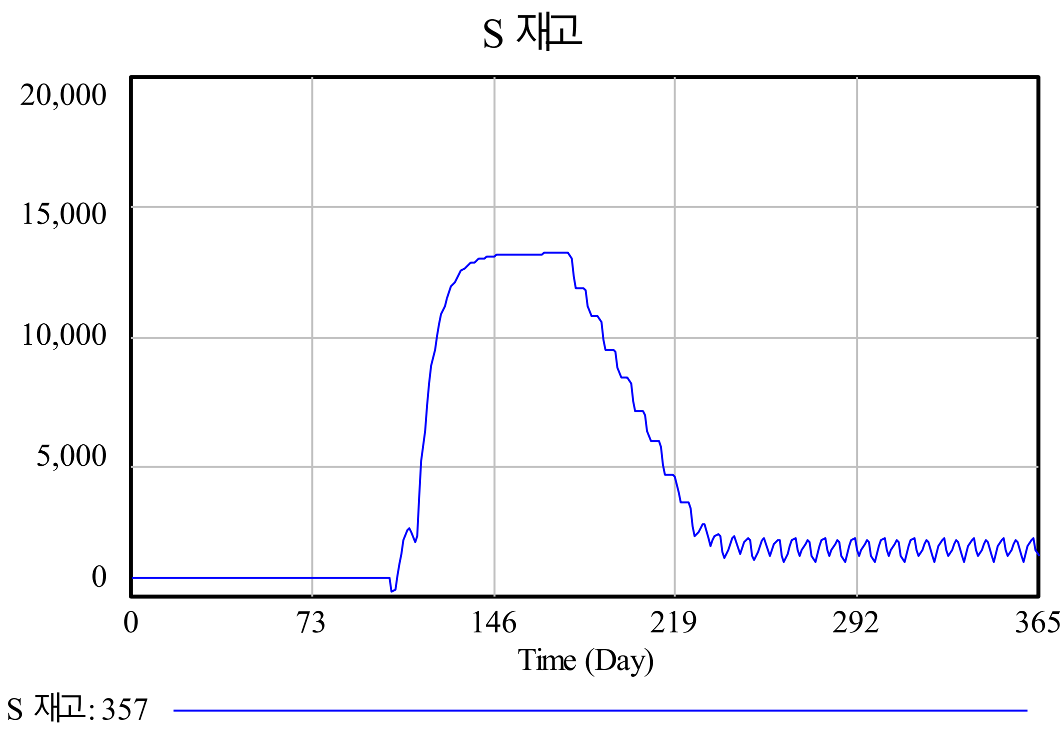
Then one wonders what value the S stock will show. Buying volume is expected to continue to amplify as it moves up the supply chain, and the lead time for S will be extended to 7 days.

<Figure 1-5> S Buying Volume Change



The maximum purchase value of S is 5,182. And it is also peculiar that the purchase volume is zero for more than 100 days. They order 5,182 pieces at a time and keep the order at zero because they are too much in stock. If it is possible to cancel the order, the inventory will return to equilibrium much sooner. Looking at S's inventory, it would be even more ridiculous.

<Figure 1-6> S Inventory Change



The average S inventory is 4,068 units, and the maximum value is 13,209 units. Unexpectedly, the average and maximum are small.

<Table 1-2> Averages and Maximums of R Inventory, M Inventory, and S Inventory

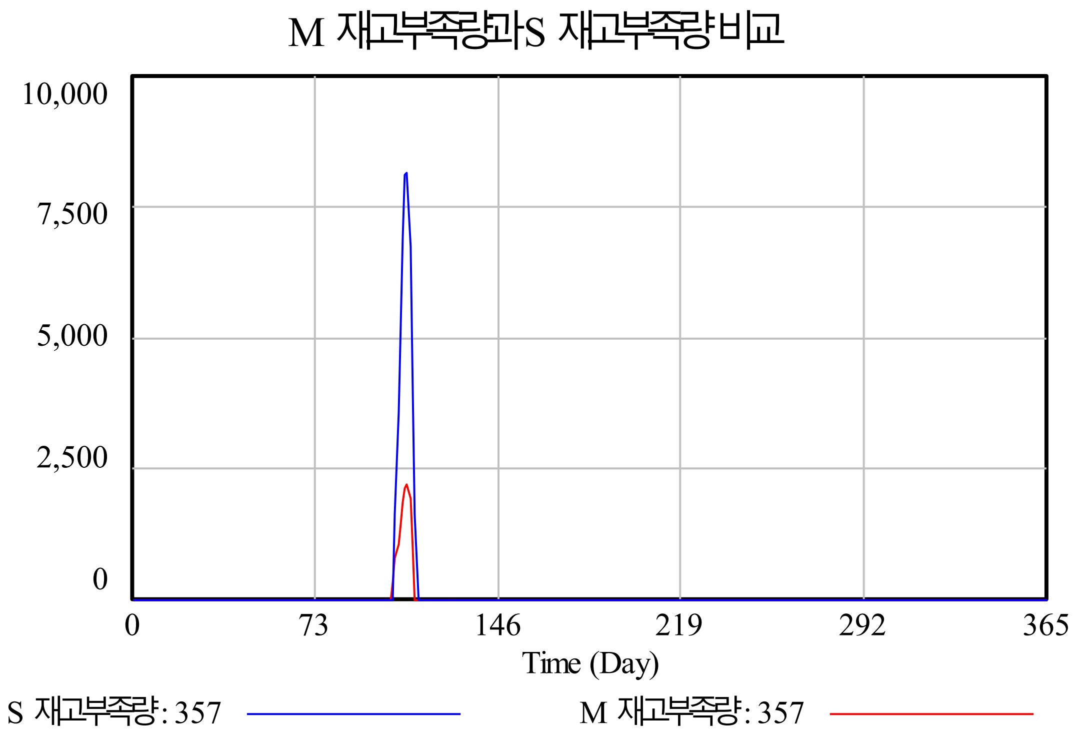
	average	Maximum value
S Stock	4,068	13,209
M Stock	2,130	11,533
R Stock	538.84	2,009

The average value of M stock compared to the average value of R stock is about 3.95. In comparison, the average value of S stock compared to the average value of M stock is about 1.9. Even at the maximum value, it is only about 5.76 times to about 1.15 times. Why has this amplification been mitigated?

First, the lead time did not increase consistently. The lead time for R was set at 3 days, the lead time for M was set at 5 days, and the lead time for S was set at 7 days. So the increase from 3 days to 5 days is quite a large increase, but the increase from 5 to 7 days is relatively small.

Second, M is affected by the supply of S, but S is in unlimited supply. M ordered because it was out of stock, but S couldn't give it because it was out of stock. If there was another supplier upstream of S, i.e. a four-stage supply chain, the amplification would be even greater.

<Figure 1-7> S Inventory Shortage vs. M Inventory Understock



Stockouts of S and M are occurring at the same time. This shows that when M was out of stock, S was also out of stock and could not supply. Therefore, M is affected by downstream and upstream inventories. On the other hand, the stock of S is only affected by downstream. Since there is no upstream impact, it shows lower inventory and overshoot than expected .

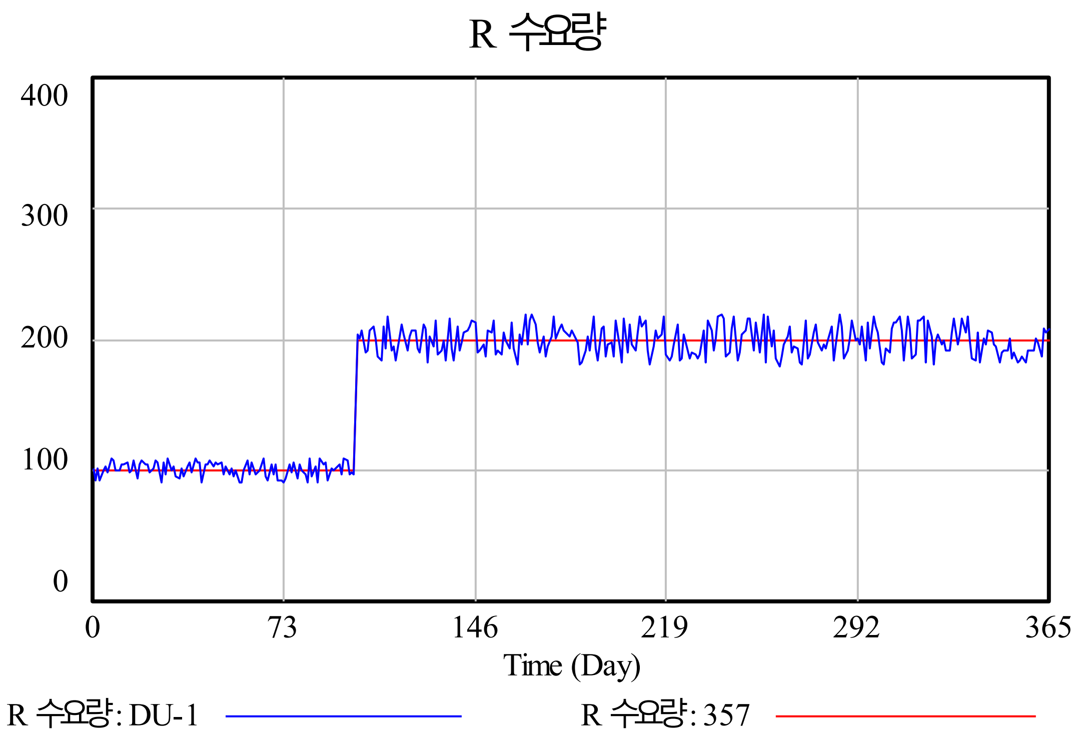
2) Three-stage supply chain model with demand uncertainty

In the models covered so far, there was little demand uncertainty. Demand only doubled once every 101 days. This is also uncertain, and the impact on the supply chain is significant. In this section, we will compare the previous model with how everyday demand uncertainty affects the supply chain. The other parameters are all the same as the model in <Figure 1-1>, and only the R demand has been changed as follows:

R Demand = (100+STEP(100, 101))*RANDOM UNIFORM(1-VOLATILITY coefficient, 1+VOLATILITY coefficient, 3456)

The volatility coefficient is a newly included variable that is limited to a value between 0 and 1. When the volatility coefficient is set to 0.1, the R demand amount is shown in the following figure.

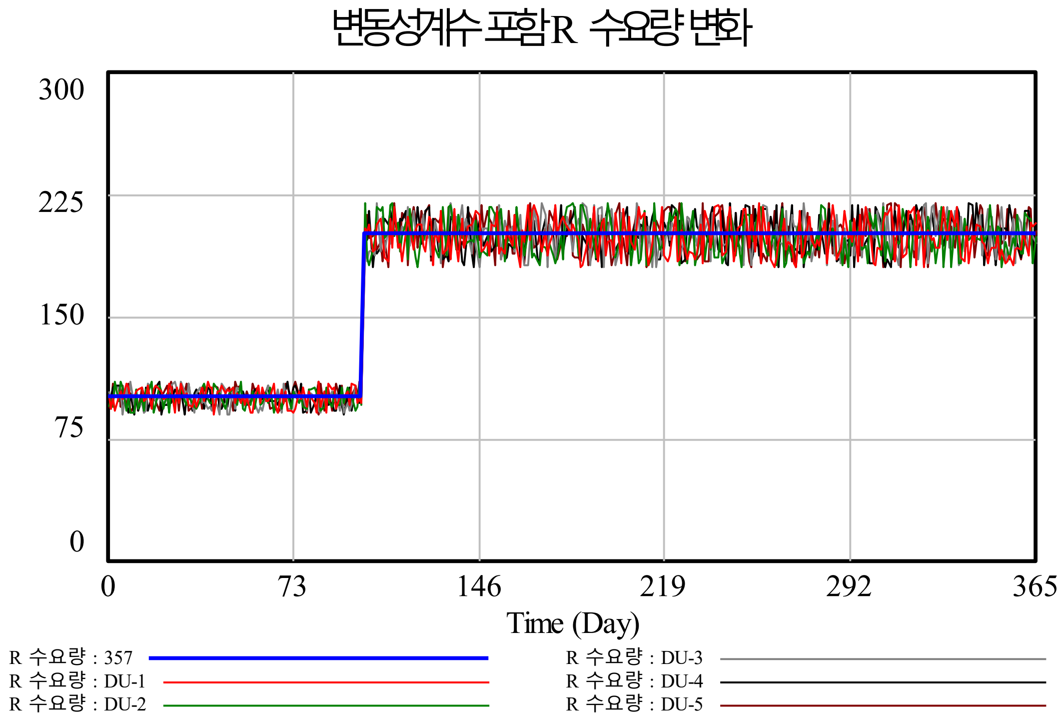
<Figure 1-8> Change in R demand when volatility is given



The red line is the R demand of the model in Figure 1-1> < does not include the variability coefficient. In comparison, the blue line is jagged. During the first 101 days, the fluctuation is small, but for the rest of the year, the fluctuation is relatively large. This is because the same volatility coefficient was applied, but as a ratio. The last 1111 in the formula is the seed number, and you can specify any four digits. And DU-1 under <Figure 1-8> is the name of the vensim data file that stores when a volatility of 10% is assigned.

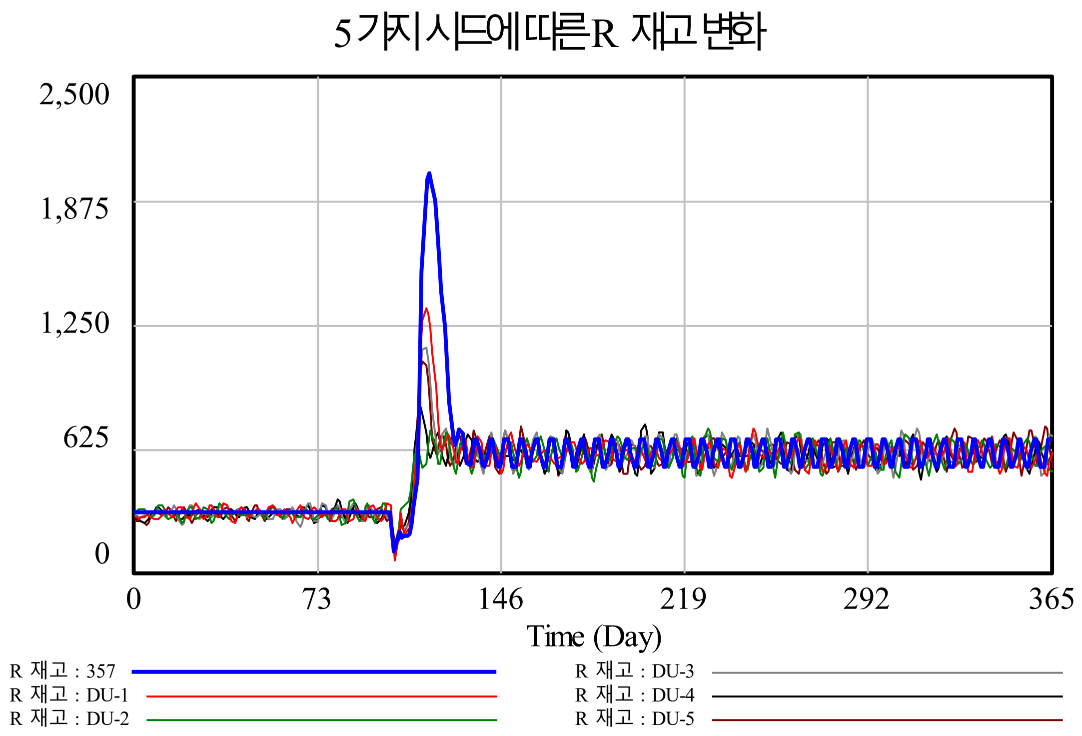
R The seed number of the demand amount was different and simulated. Simulation was performed on five seeds by storing the seed number 1111 in DU-1, 2222 in DU-2, and so on. In <Figure 1-9>, the blue straight line in bold indicates when there is no volatility coefficient.

<Figure 1-9> Changes in R demand when given seed volatility



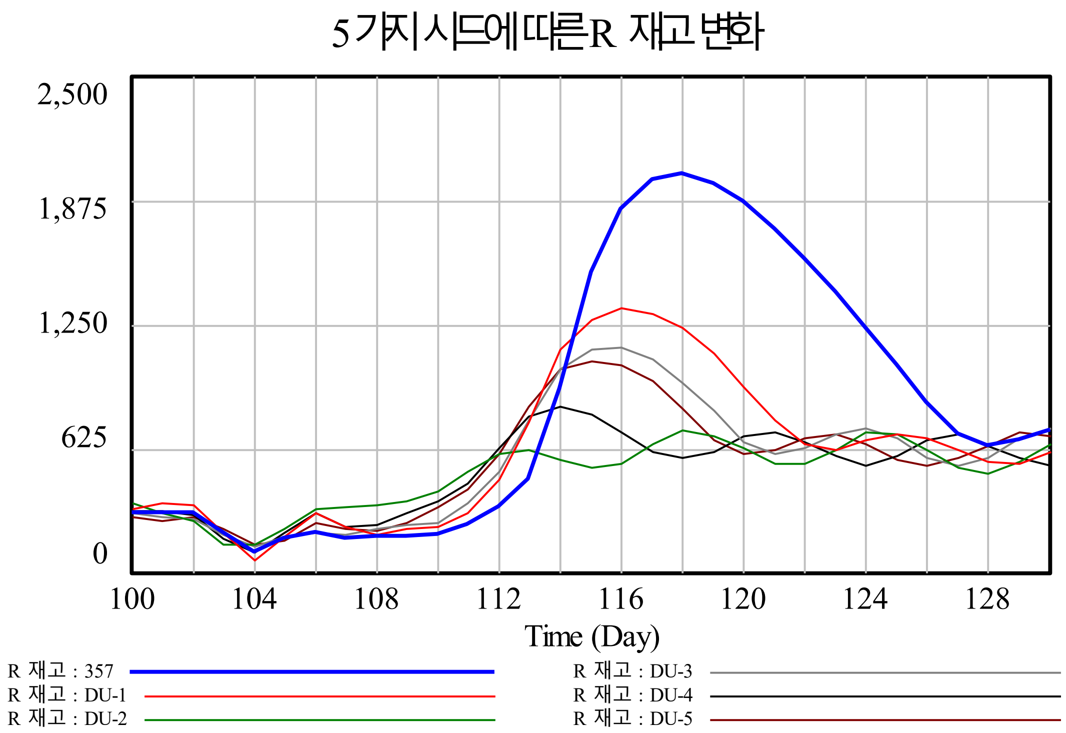
Let's look at the R inventory according to the five seed changes. It came out as shown in the following figure.

<Figure 1-10> Change in R inventory according to 5 seeds when given volatility coefficient



<The figure in Figure 1-10> is a little complicated, so if you zoom in between 1 00 and 130 days, it looks like the following <Figure 1-11>.

<Enlarged version of Figure 1-11> <Figure 1-10>



If you look closely at <Figures 1-11> you will notice something unusual. The overshoot of R inventory is highest in Bensim data file 357. However, this blue line does not reflect the volatility coefficient in demand. It is a case of climbing one flight of stairs in the shape of a slippery staircase. In other cases, it is a jagged R demand.

Despite further changes in demand, the overshoot has decreased. Overshoot isn't the only big thing. The average inventory for the entire period also differed as shown in the following table.

<Table 1-3> Basic statistics such as average of R inventory

Data File Name	CountCount	Minimum Min	Maximum Max	Avg. Mean	ModeMedian	Standard deviation StDev	Norm
357	366	100	2,009	538.84	535.20	254.22	0.4717
DU-5	366	138.94	1,069	517.30	567.06	163.61	0.3162
DU-4	366	106.45	837.09	512.83	573.33	153.96	0.3002
DU-3	366	130.30	1,131	519.09	562.47	168.38	0.3243
DU-2	366	139.04	730.24	508.34	557.94	146.92	0.2890

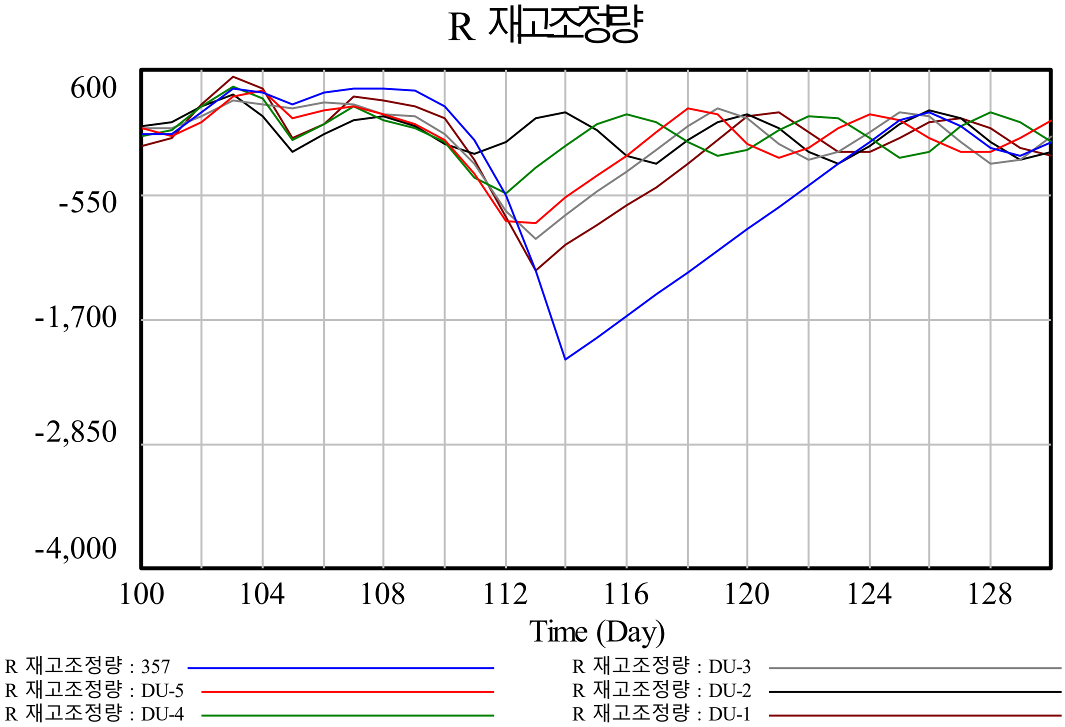
DU-1	366	65.24	1,332	518.46	569.65	176.25	0.3399

The average of 357 is 538.84, which is more than the other cases. The maximum value determines the size of the overshoot, which is 2,009 for 357, more than any other case. R inventory between 0 and 100 days or between 150 and 365 days has a value similar to 357 in the other case. It's just that the overshoot is big.

Each participant in the supply chain controls the supply line and inventory. The target supply line and target inventory are set, and if the supply line and inventory are less than this, it is replenished, and if it is more, it is deducted through the one-day volume forecast. Generate an adjustment in the amount of inventory, and purchase positive water by comparing it with the daily demand (requirement). If the inventory or supply line is less than the target, they buy immediately, but in many cases, they compare the one-day requirement with the absolute value. Because of this, the 357 with no change in demand volume has a larger overshoot.

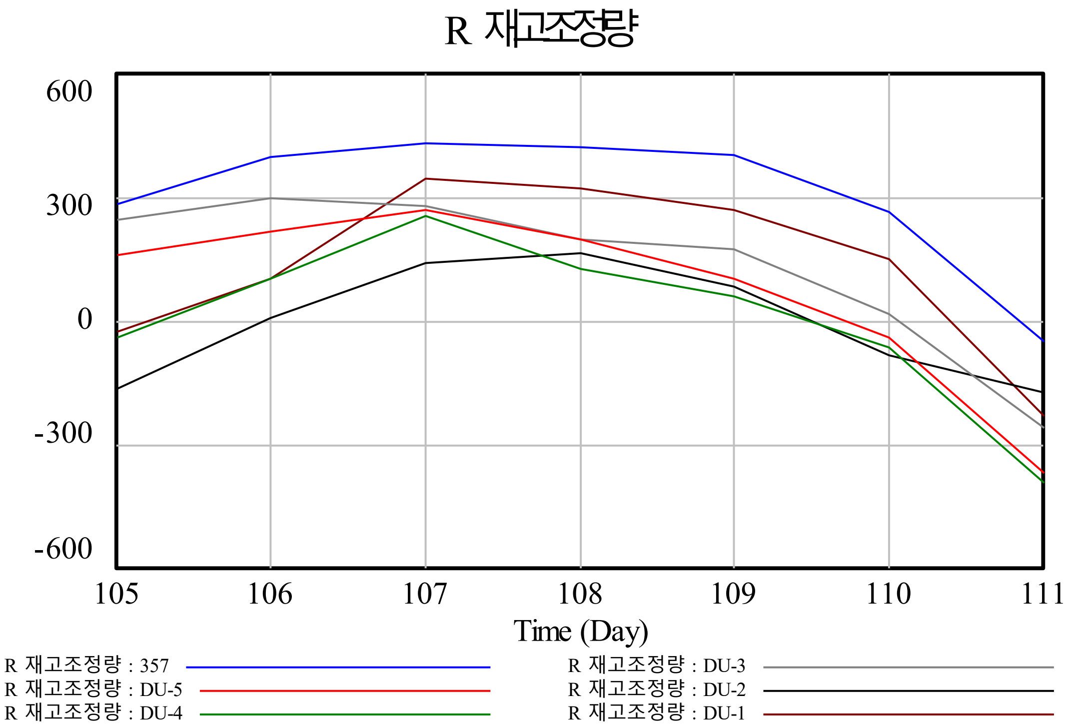
In the case of 357, the amount of demand was constant at 1 00 from 0 to 100 days. Therefore, there was no difference between the target inventory and the amount of inventory. There was also no difference between the target supply line and the supply line. Then, on the 101st, demand suddenly rose by 100 to 200. If the control mechanism was in operation, the inventory adjustment value of R is likely to be negative. Because if there is a +, remove it quickly, and if there is a -, remove it late. R The inventory adjustment value from 100 to 130 days is as follows.

<Figure 1-12> R Inventory Adjustments for 100-130 Days



The blue line is the case with 357. It is a line that drops below 2,000. However, the starting point should not be placed at the point where it falls below 2,000. This occurred at the peak of the overshoot.

<Figure 1-13> R Inventory Adjustments for Days 105-111



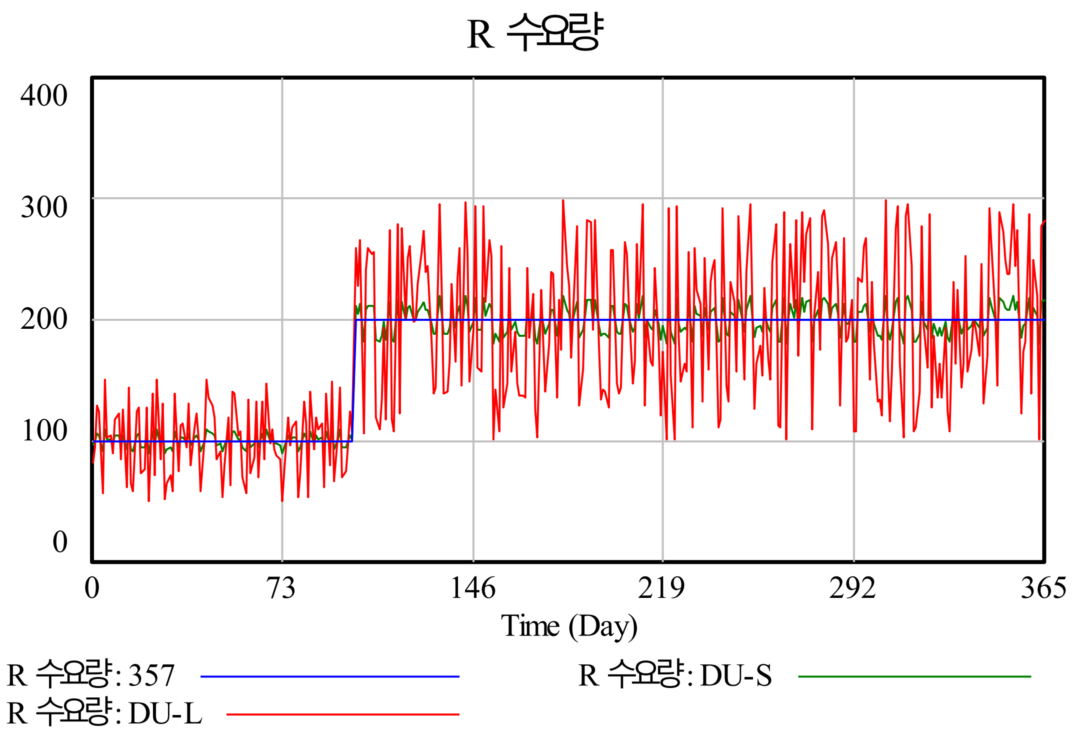
1 R inventory adjustments between 05 and 111 days are larger than other seeds, as shown in <Figures 1-13>. In other words, there was a lot of adjustment, but it was shipped late because of the lead time, and the adjustment amount was not resolved, and this time too much came in, causing the R inventory adjustment to fall. Over 7 days (105 days to 11days), the average R adjustment for 357 files was 306.78. Files with different seeds were 132.59, -4.327, 135.12, 6.583, and 76.55 (DU-1 from the front, DU-5 from the end). After all, it is due to the control mechanism (negative loop) and delay.

The hypothesis that overshoot will be greater when uncertainty is added to demand (given variation) should be rejected. It will be necessary to discuss whether the control loop is working, but for now, the direct link to demand uncertainty and rising inventories seems to be unlikely.

3) Changes in supply chain inventories when demand uncertainty increases

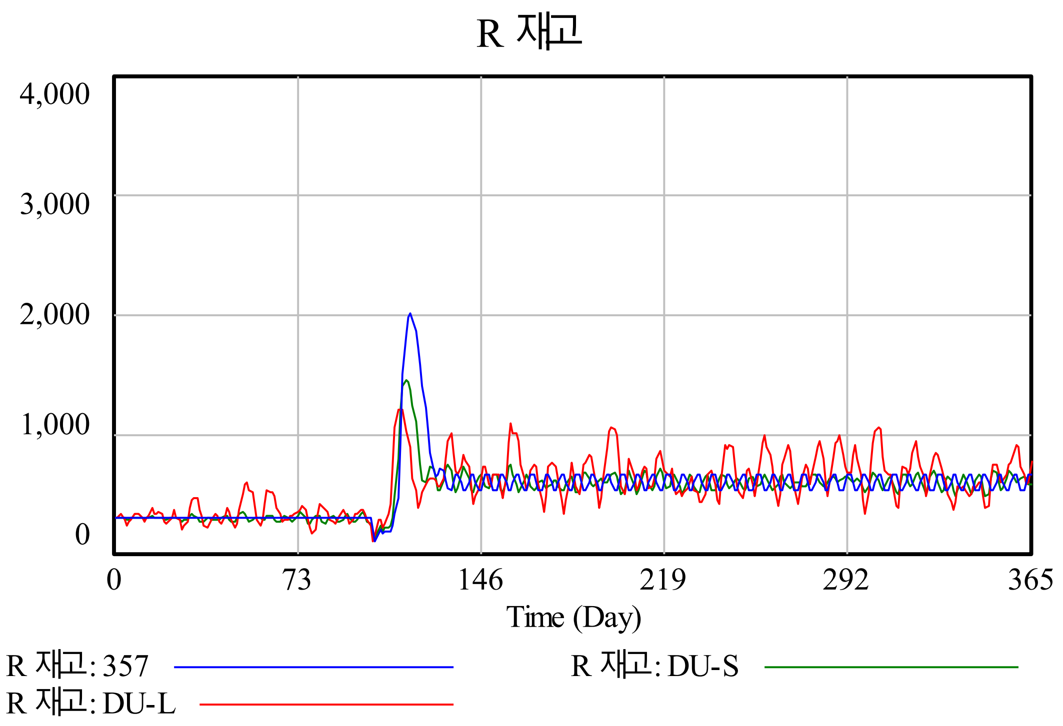
This time, we will look at the change in inventory when the volatility coefficient of R demand is set to 0, 0.1, and 0.5. First, the R demand amount when the volatility coefficient is assigned respectively is shown in the following figure.

<Figure 1-14> R demand change according to the volatility coefficient



In <Figure 1-14>, the blue line is 357 (with a volatility coefficient of 0), and the red line with a large amplitude has a volatility coefficient of 0.5. The averages of the reproduced demand volumes were approximately the same, at 172.40, 172.39, and 172.33. R inventory according to each demand is shown in the following figure.

<Figure 1-15> R inventory change according to volatility coefficient



As expected, the largest overshoot is 357, that is, when the volatility coefficient is zero. The average inventory for the entire period is shown in the following table.

< Table 1-4> R inventory values according to the volatility coefficient

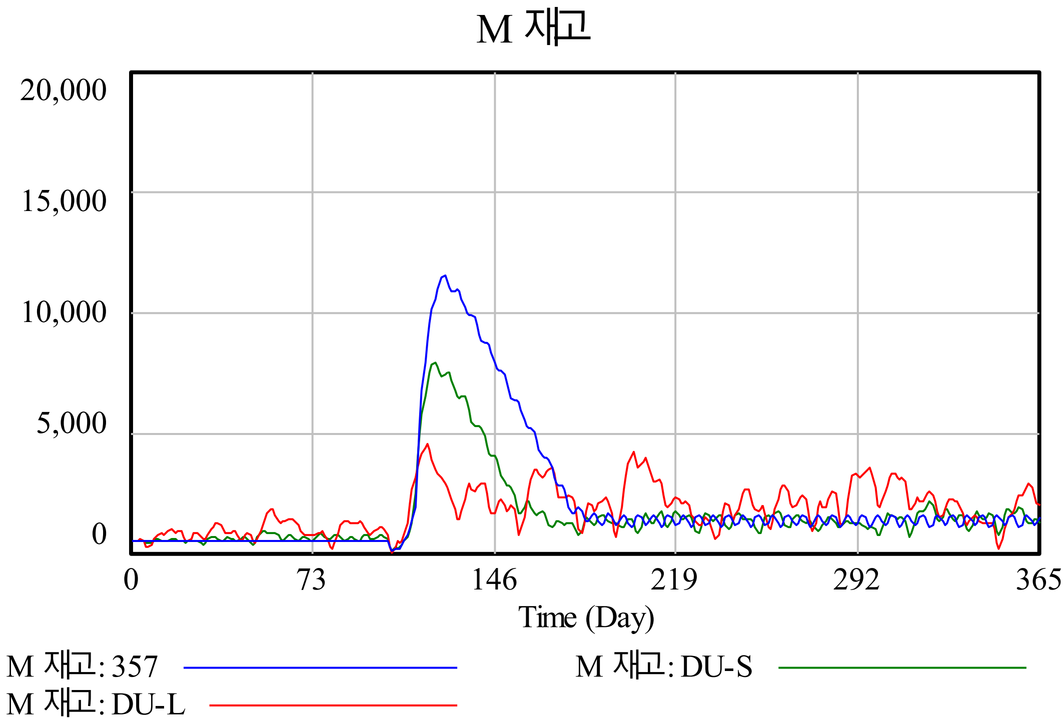
Volatility coefficient	average	Standard deviation	Minimum	Maximum value
0	538.84	254.22	100	2,009
0.1	524.75	190.34	144.18	1,451
0.5	576.24	224.46	111.19	1,212

The volatility coefficient is 0. 1 had the lowest average inventory. A higher volatility coefficient does not mean an increase in average inventory. Separating uncertainty into big uncertainty and small uncertainty can lead to interesting results. Assume that the large uncertainty is an increase in the calculation, and that the small uncertainty is the deviation that occurs on a daily basis. When great uncertainty occurs, it increases the amount of inventory. The reason for this is overshoot. It can be hypothesized that the greater the small uncertainty, the higher the inventory.

Verification of this should be verified by more random numbers. Since it is not a thesis, the verification process is omitted. For those preparing a dissertation, developing it might make a good thesis.

We also need to look at M inventory as the volatility coefficient changes. This is because it may differ from the inventory change of R.

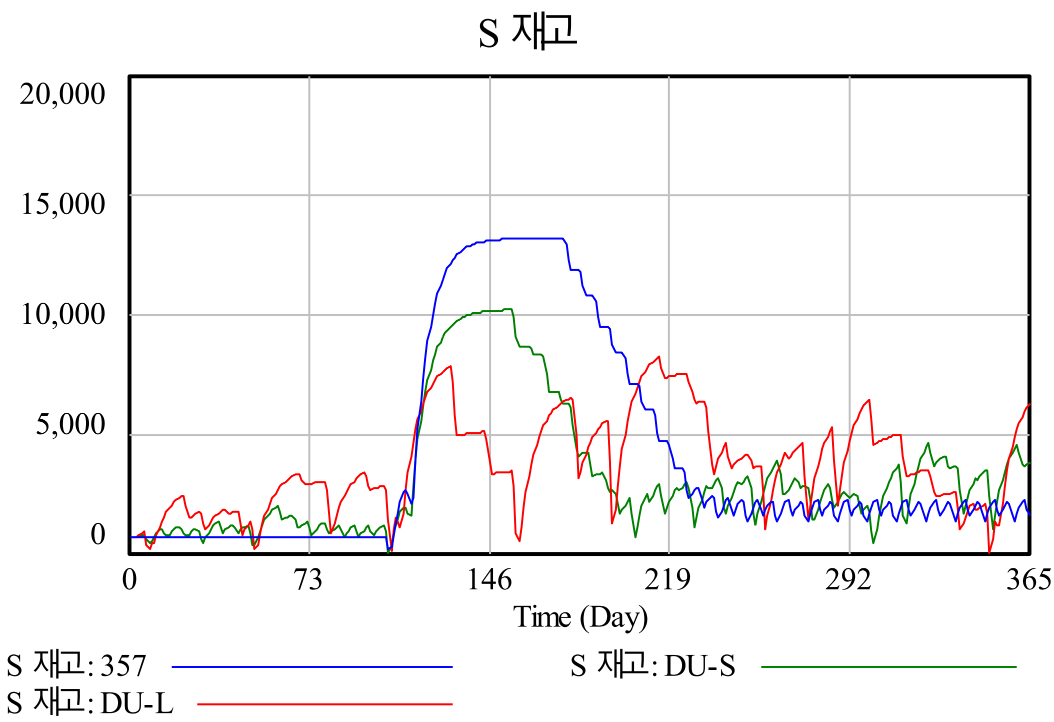
<Figure 1-16> M inventory change according to volatility coefficient



The average of M inventory was 2,130 (2,659) with a volatility coefficient of 0 (357 files), 1,613 (1,548) with a volatility coefficient of 0.1 (DU-S), and 1,843 (952.35) with a volatility coefficient of 0.5 (DU-L). At the second stage of the supply chain (M), the overshoot, as with R, was greatest when the volatility coefficient was zero, and the average of M inventories was also the highest. The influence of the overshoot was greater in M. As small uncertainties grew, inventories increased. Whether the difference is significant should be tested on more seeds.

Finally, we look at the S inventory change. The volatility coefficient was left at three.

<Figure 1-17> S inventory change according to volatility coefficient



In <Figure 1-17> the highest is when the volatility coefficient is zero. The next largest overshoot is when the volatility coefficient is 0.1. Finally, the overshoot is caused by a split when the volatility coefficient is 0.5. Even in the presence of small uncertainty, a small overshoot appears when the volatility coefficient is 0.5. This affects the amount of inventory. In the case of S, there is no restriction on supply capacity, so it was suggested earlier that the overshoot occurs relatively small compared to M. Nevertheless, because of the overshoot, it showed a standard deviation from the following stock mean.

Table 1-5 < S inventory values according to > volatility coefficient

Volatility coefficient	average	Standard deviation	Minimum	Maximum value
0	4,068	1,935	186.66	13,209
0.1	3,254	2,738	59.26	10,231
0.5	3,734	1,987	58.25	8,274

This chapter defines the most basic supply chain in three stages and describes the modeling process.

It is assumed that each participant S, M, and R has a loop that controls the supply line and inventory. And these are the most commonly accepted loops.

The lead time was considered to be longer upstream. R-M-S was assumed to be 3, 5, and 7 days in order. Usually, the further upstream, the longer the lead time. Forecast periods and safety levels were also based on their lead times. Simulations were performed for 0 to 365 days on R demand (exogenous variable) using the step function.

In the simulation process, two types of uncertainty were distinguished. It was divided into large uncertainty, which is in the form of steppe functions that increase cascadingly, and small uncertainty, which is in the form of deviations that occur daily. Again, the small uncertainty was divided by 0.1 and 0.5 using the volatility coefficient.

Simulations showed that great uncertainty had a significant impact on the supply chain. When uncertainty occurred on a single day and the volatility coefficient was zero, which did not occur for the remaining 365 days, there was a surprisingly large overshoot in inventory . Since it is not exposed to small uncertainties, it has the disadvantage that it takes a long time for the inventory adjustment to be resolved.

The size of the overshoot due to the great uncertainty was indicated by the very large value of M in the middle. S, located upstream of the supply chain, was, of course, a high number in absolute terms, but in terms of the rate of increase and decrease, the rate of increase from M to S was not greater than the rate of increase from R to M. This is probably because S is premised on an unlimited supply. This is because in the case of M stuck in the middle, both upstream and downstream stocks are affected.

There is no standard for distinguishing between small and large uncertainties. If the volatility coefficient of small uncertainty is 1, it is equivalent to large uncertainty occurring every day. Therefore, this distinction is arbitrary. And from the decision-maker's point of view, we don't know whether these changes will last or end at once, and the criterion of great uncertainty is vague when it is more than its size. Looking at the pattern that has occurred, it will be possible to distinguish between systematic and non-systematic uncertainty . Large uncertainty in the form of a step function can be named as systematic uncertainty, and small uncertainty as unsystematic uncertainty. However, this too is difficult for decision-makers to judge within the process.

It's also a story that goes hand in hand with prediction accuracy. When we identify the characteristics of uncertain factors such as trends or cyclical factors, they change probabilistically. If it is probabilistic, the risk can be assessed. Therefore, it is necessary to reduce more factors, leaving only uncertainty that can no longer be foreseen. These discussions will continue in this book.

Chapter 2

The impact of lead time on the supply chain

Leadtime Change on the Supply Chain

It's no exaggeration to say that much of supply chain strategy is related to lead times. In other words, if you understand how reduced lead times affect your supply chain, you've learned more than half. But it's just as hard.

Lead time is literally ahead of time. In the supply chain, it typically takes time for an order to be placed and for the item to be shipped and available for use or sale. This is called lead time. Therefore, lead time involves many time factors. In general, it consists of time related to the flow of goods, time related to information flow, and time related to decision-making such as administration. It would be easier to understand if it was the sum of the time to change the order, receive information, make decisions, and send supplies.

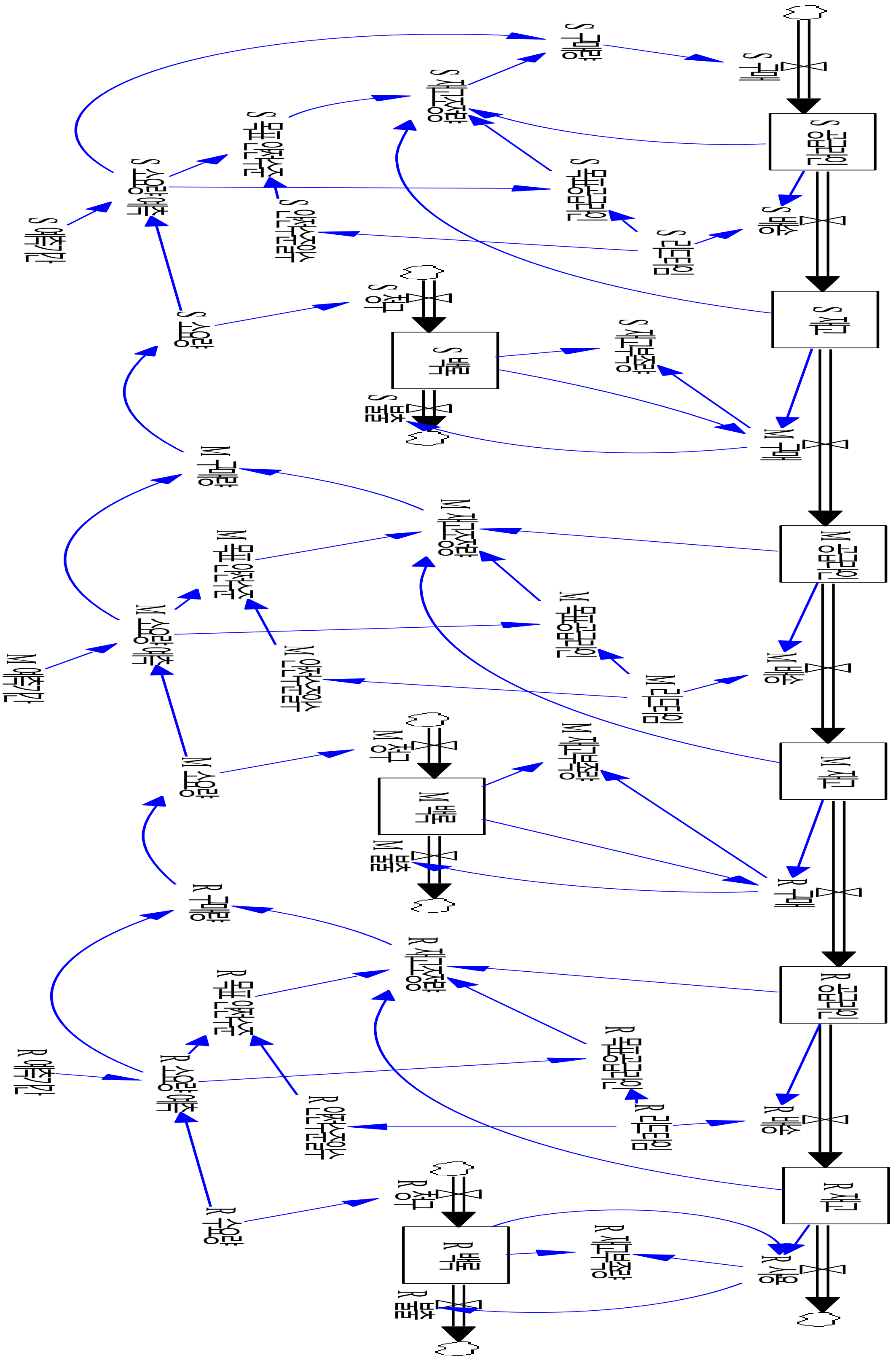
If you reduce the lead time by one hour (unit), the effect is the same whether you reduce the information time or the material time. However, it is less expensive to reduce information time by one hour than to reduce logistics time by one hour. The cost of building an information system may be high, but the unit cost is not high because it is used for numerous trading activities. However, to shorten the logistics time is expensive. Switching from traveling by boat to a car, or by plane, costs much more. Depending on the distance, it depends on the item, but in terms of transportation costs, it is often 50 times different. There is no difference in utility due to time reduction, but if the related cost is low, it is reasonable to choose an efficient method. Therefore, many companies prioritize shortening the information flow time.

Let's start with a fundamental question. Does less lead time mean less inventory? Does customer service improve? How much does it improve if it improves? The goal of this chapter is to make a rough guess using our typical supply chain model.

1) Reduced lead time by 1 day

To save you the trouble of going back to the front and looking for a model, the basic model is presented in Figure 2-1> <.

<Figure 2-1> Three-stage supply chain model as a basic model

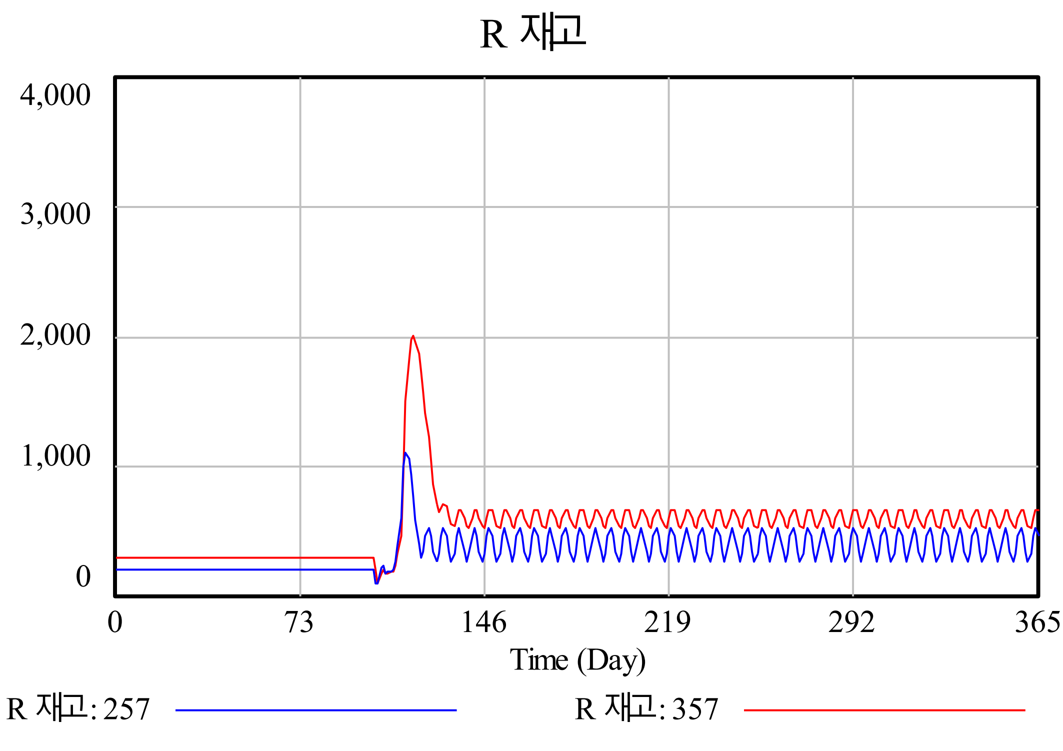


R's lead time, target supply line, target safety level, and required quantity forecast all used 3 days (unit time). M used 5 days and S used 7 days. It was even said that it was common for the beat to slow down as you went upstream.

The demand for R uses the same value that was used at the beginning of Chapter 1. It was assumed that there would be 1 00 demands per day for the first 100 days, and then 200 demands for 101 to 365 days. The name of the data file used to simulate this is 357. It was vdf.

First, let's start with the lead time of R to see the impact of reduced lead times. Here, the lead time of R refers to the time it takes to receive from M. It is not the customer side part of R. Look at how a one-day reduction in lead time impacts the supply chain. The reduction from 3 days to 2 days not only reduces the R lead time, but also the R target supply line, R target safety level, and R forecast period.

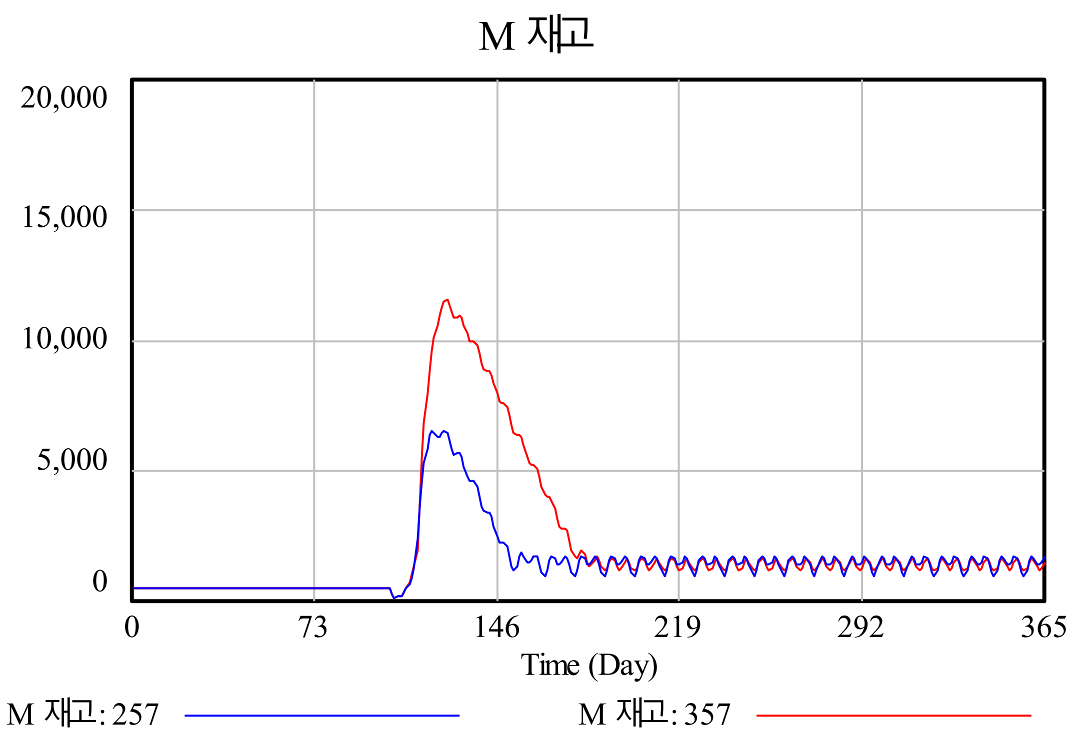
<Figure 2-2> R inventory changes due to 1-day decrease in R lead time



In <Figure 2-2>, the blue line is 257. R This is the case when the lead time, etc. is reduced from 3 days to 2 days. Overall, inventory has become less. The size of the overshoot has also decreased. For 357, the average R stock was 538.84, compared to 347.70 for 257. R's inventory decreased by approximately 35%. The reduction in lead time from 3 days to 2 days is also a 33% reduction, so we can see a similar decrease in inventory. When the R lead time was increased to 4 days (all other procedures were equal), the average R inventory was 738.25. It increased by about 37 percent.

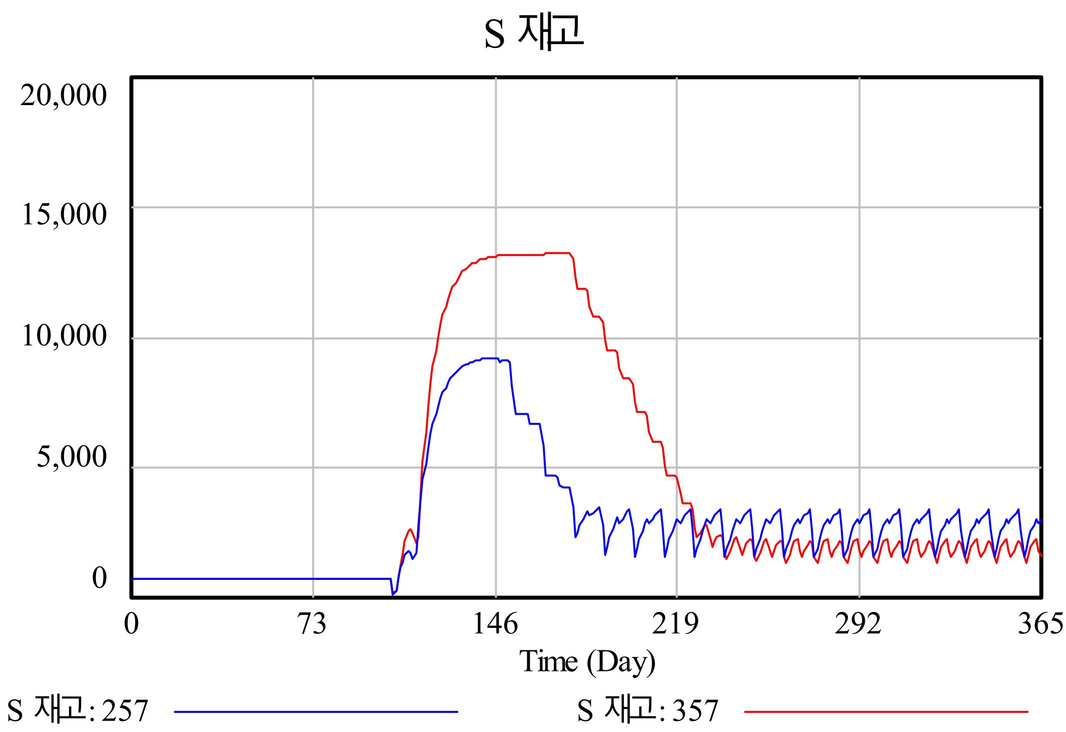
M inventories also declined. There was no change in the lead time of the M. Only the lead time of R changed.

<Figure 2-3> M inventory due to changes in R lead time, etc .



When R lead times, etc. (the same applies to forecast periods, target times) were reduced from 3 days to 2 days, M inventory decreased from an average of 2,130 to 1,468, a decrease of about 31%. It is surprising that even M inventory has been reduced by more than 30%. At the beginning and end, the two lines almost coincide. It's the same level. The difference in the overall average by more than 30% is in the overshoot section. The M stock overshoot at 357 was 11,533, but the overshoot at 257 was 6,541, down about half.

<Figure 2-4> S inventory due to changes in R lead time, etc.

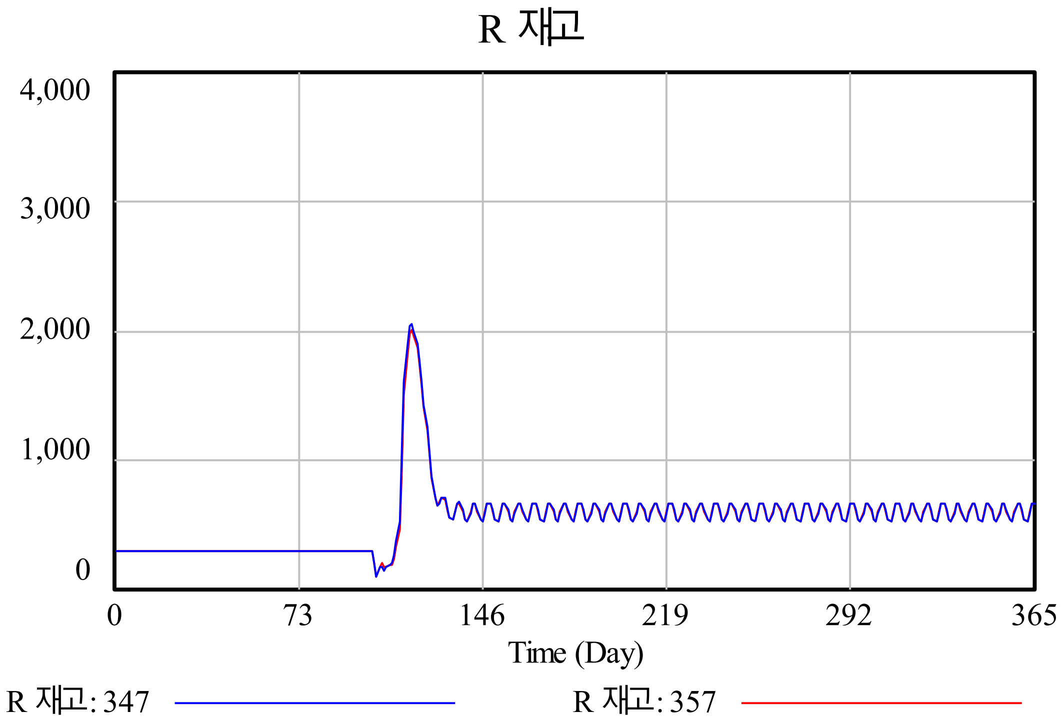


S inventories also declined. For 357, the average was 4,068, and for 257, it was 2,854. It decreased by approximately 30%. Overshoot also decreased by 30%, from 13,209 to 9,233.

Reducing R's lead time by one day (33%) also reduces the inventory of M and S upstream of the supply chain by about 30%.

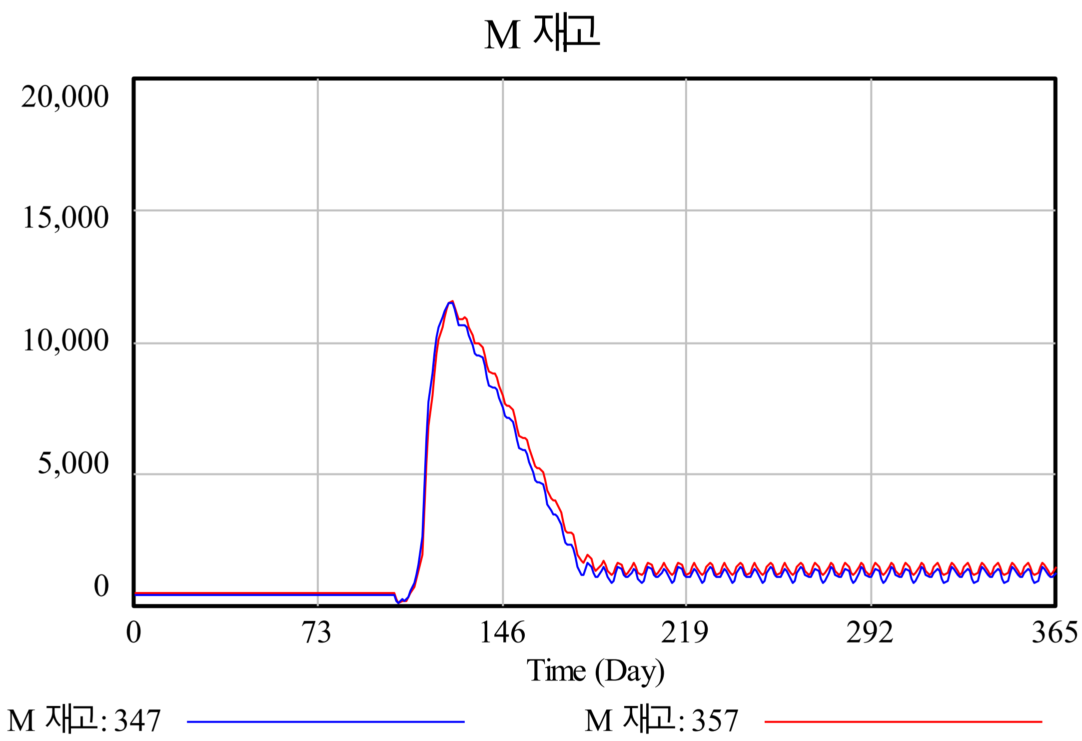
This time, let's reduce the lead time of M from 5 days to 4 days. The expression of lead time is because not only the lead time but also the forecast period and target level are taken into account. Even on the same 1 day, a decrease from 3 to 2 days is a 33% reduction, and a decrease from 5 to 4 days is only 20%. The following <Figure 2-5>, <Figure 2-6>, <Figure 2-7> show R inventory, M inventory, and S inventory when M lead time is reduced by 1 day.

<Figure 2-5> R inventory when lead time for M is reduced from 5 days to 4 days



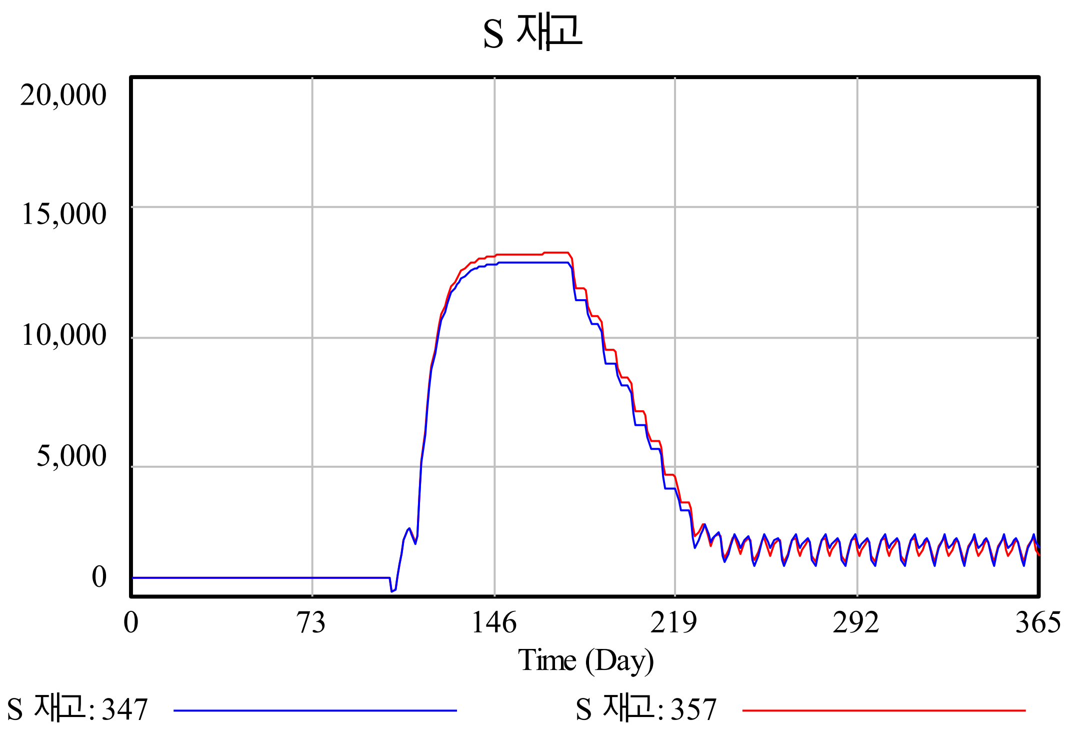
The average R inventory increased slightly from 538.84 at 357 to 540.78 at 347. Since it is a very small car, the difference is not significant.

<Figure 2-6> M inventory when lead time of M is reduced from 5 days to 4 days



Since M reduced its own lead time, it was expected that there would be a significant difference, but what actually appeared is only a very slight difference, as shown in <Figure 2-5>. M inventory averages decreased by about 8%, from 2,130 to 1,957. Overshoot decreased only slightly, from 11,533 to 11,495.

<Figure 2-7> S inventory when lead time of M is reduced from 5 days to 4 days



S inventories fell 2% from an average of 4,068 to 3,979. The overshoot decreased from 13,209 to 12,898. The effect of reducing R lead time is not as good.

Nine models were made with different lead times.

Table 2-1> < Average and maximum inventory values for each participant according to lead time changes

Model	R Stock		M Stock		S Stock		Total Stock	Total Lead Time
	average	Maximum value	average	Maximum value	average	Maximum value		
333	560	2,497	1,506	8,643	2,509	6,993	4,575	9
257	348	1,108	1,468	6,541	2,855	9,233	4,671	14
355	542	2,085	2,009	10,786	3,102	10,488	5,653	13
337	544	2,129	1,625	10,330	3,526	11,898	5,696	13
347	541	2,054	1,958	11,496	3,979	12,898	6,477	14

356	540	2,047	2,106	11,250	3,899	11,868	6,546	14
357	539	2,010	2,130	11,534	4,069	13,210	6,738	15
369	531	1,774	2,294	11,192	4,662	14,519	7,487	18
457	738	2,774	2,978	15,388	5,948	16,232	9,664	16

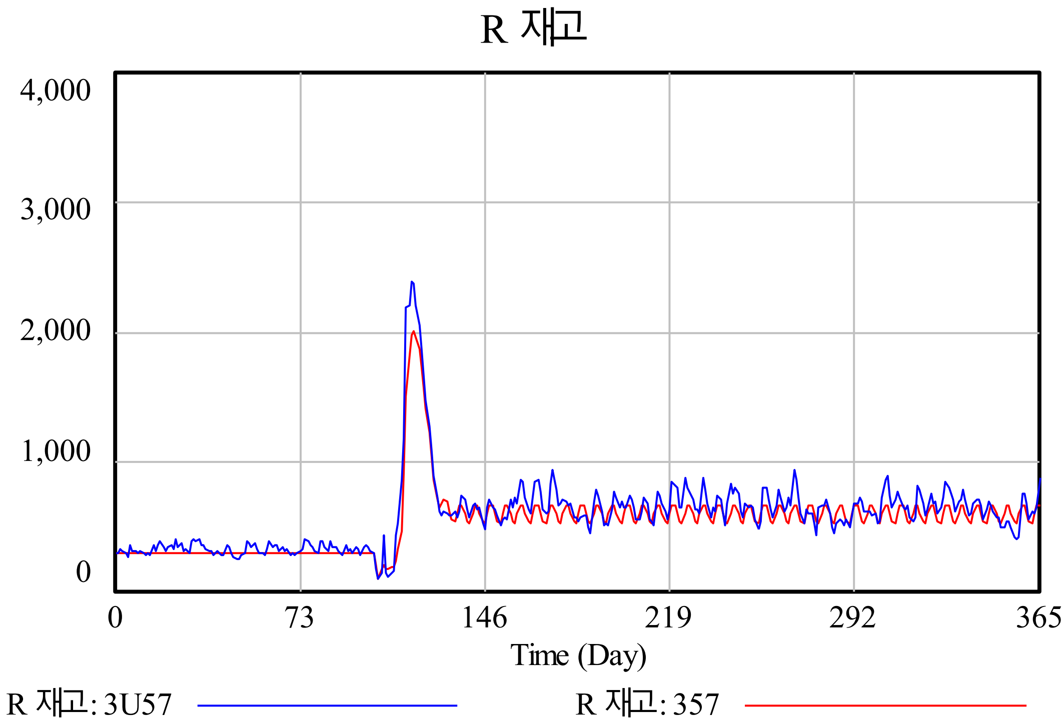
In the first column of Table 2-1> <, 333 is when the lead time of R is 3, the lead time of M is 3, and the lead time of S is 3, and the lead time of 457 at the bottom is 4, 5, and 7 in that order. The Total Inventory column says R Inventory + M Inventory + S Inventory. The total lead time is the simple addition of each lead time. In general, the shorter the total lead time, the smaller the total inventory. However, in order to reduce the lead time of 1 day, it is analyzed that it is very effective to reduce the lead time of R. As mentioned earlier, the lead time of R affects the entire supply chain evenly, but the lead time reduction upstream is that the impact on the supply chain is only itself and its own headstream.

Looking at the above models, the most efficient lead time reduction strategy is the change from 357 to 257. Reducing R's lead time from 3 days to 2 days reduces the total inventory by about 2,000 units. You can see a reduction in inventory of about 30%. The change from 357 to 347 or from 357 to 356 does not significantly change the overall inventory. Since there are about 200, it is only one-tenth of the effect of changing the lead time of R. On the other hand, in the case of 3 33, the inventory increases as you go downstream to upstream. However, the maximum value of the inventory is unusual in that the M in the middle is the most, and it is generally difficult to predict.

2) Analysis of the effects of lead time uncertainty

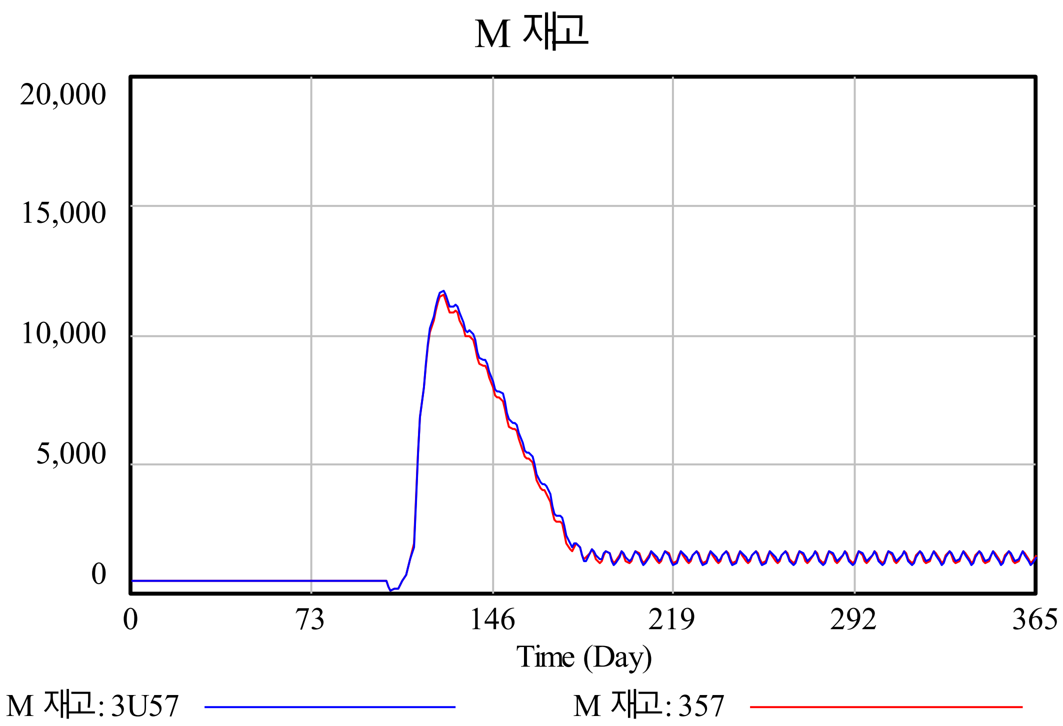
Use the model in Figure 2-1> < as it is. The R lead time was constant at 3. This was changed to Random Uniform (1.5, 4.5, 1234). This equation means that the lead time from M to R occurs evenly between 1.5 and 4.5 days each time. Various permutations are possible depending on the time, among which the random number 1234 was used. The average lead time is 3 days. For target supply lines or target safety levels, a constant of 3 was applied because the lead time average was expected to be applied. In Chapter 1, we tried to reflect the uncertainty of lead time corresponding to the coefficient of variation of demand of 0.5.

<Figure 2-8> R inventory when R lead time uncertainty occurs



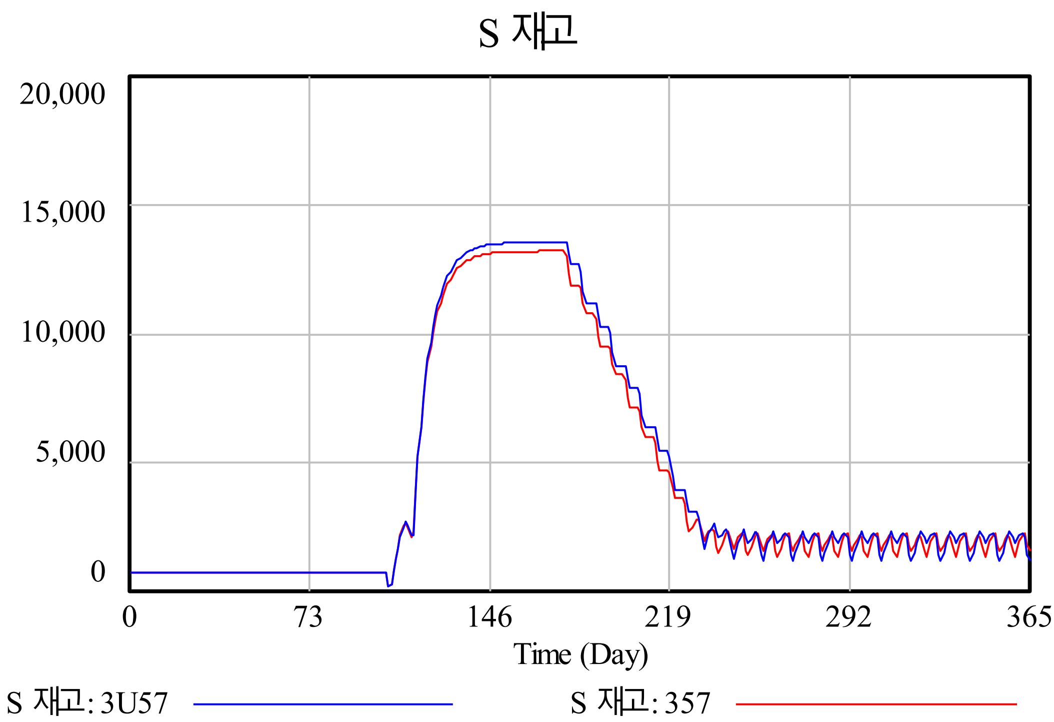
By adding volatility to the R lead time, it can be seen that the R inventory has increased. When the volatility factor was not applied to the lead time (357), the R inventory averaged 538.84 and the maximum value was 2,009. Reflecting the volatility of 0.5, the average R inventory was 590.87 and the maximum value was 2,395. Overall, it led to an inventory increase of about 10%.

<Figure 2-9> M inventory when R lead time uncertainty occurs



The average M inventory increased slightly from 2,130 to 2,168. The maximum value also increased slightly, from 11,533 to 11,746. This is in contrast to R demand volatility, which had a significant impact on M inventories.

<Figure 2-10> S inventory when R lead time uncertainty occurs



S inventories increased by about 3.6 percent from an average of 4,068 to 4,217 and a maximum of 13,209 to 13,549, an increase of only about 2.5 percent.

As such, the uncertainty of lead time does not appear to affect the increase or decrease of inventories as much as the uncertainty of demand, because the author modeled it that way. When reflecting the volatility of demand, both the target supply line and the target safety level were affected, but when reflecting the lead time, it is believed that it was because the target values of the stock price were stabilized. The actual lead time is volatile, and it may be an overly rational human view to reflect this by picking up the average from God's point of view.

Therefore, a variable called "R perceived lead time" was created and reset to the following formula:

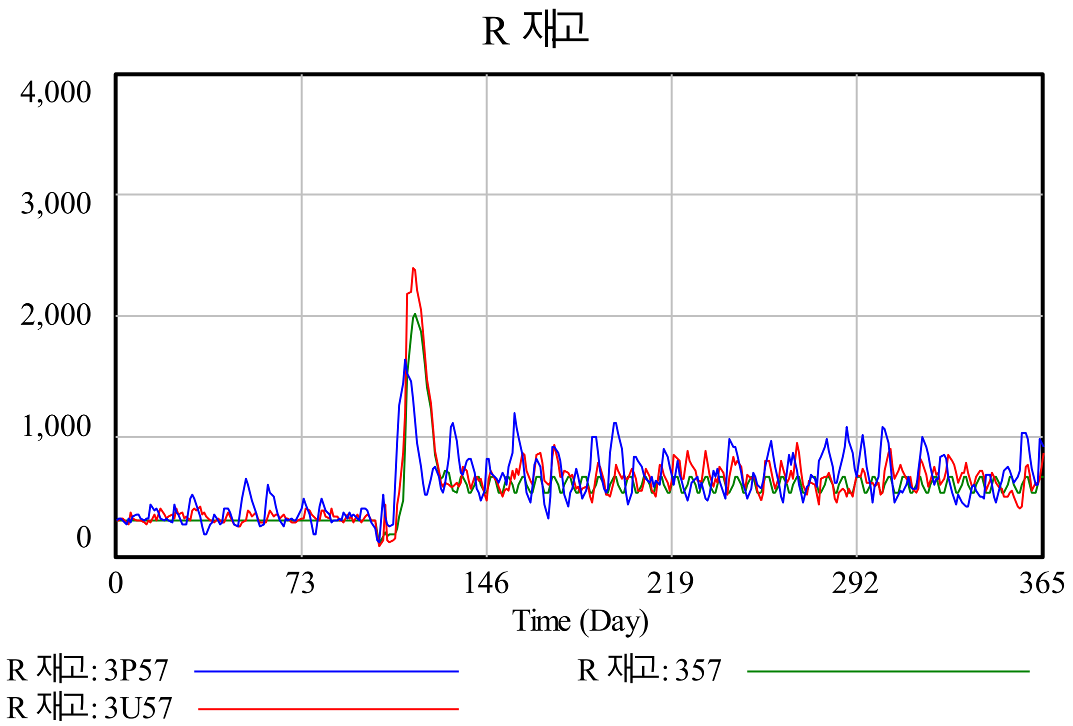
R Perceived Lead Time = SMOOTH(R Lead Time, 3)

R Target Supply Line = R Perceived Lead Time*R Prediction of Consumption

R safety level days = R perceived lead time

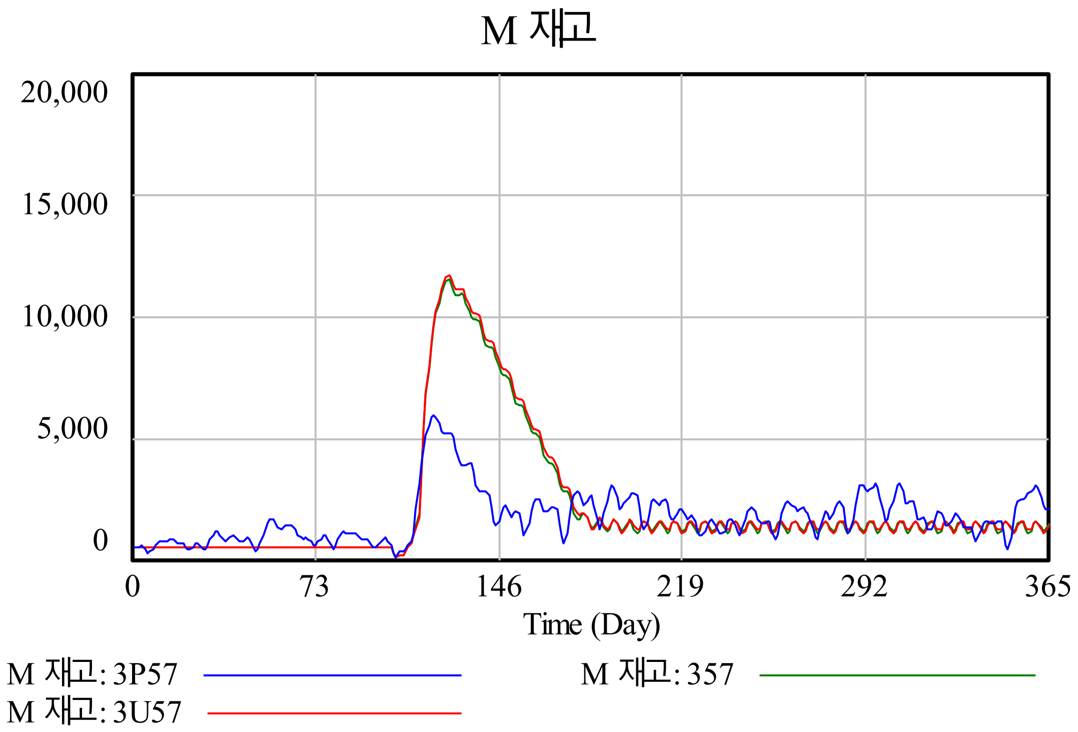
Then I entered the Vensim data file as 3P57 and ran the simulation.

<Figure 2-11> Change in R inventory when R perceived lead times are generated and applied to target supply lines and target safety days (3P57)



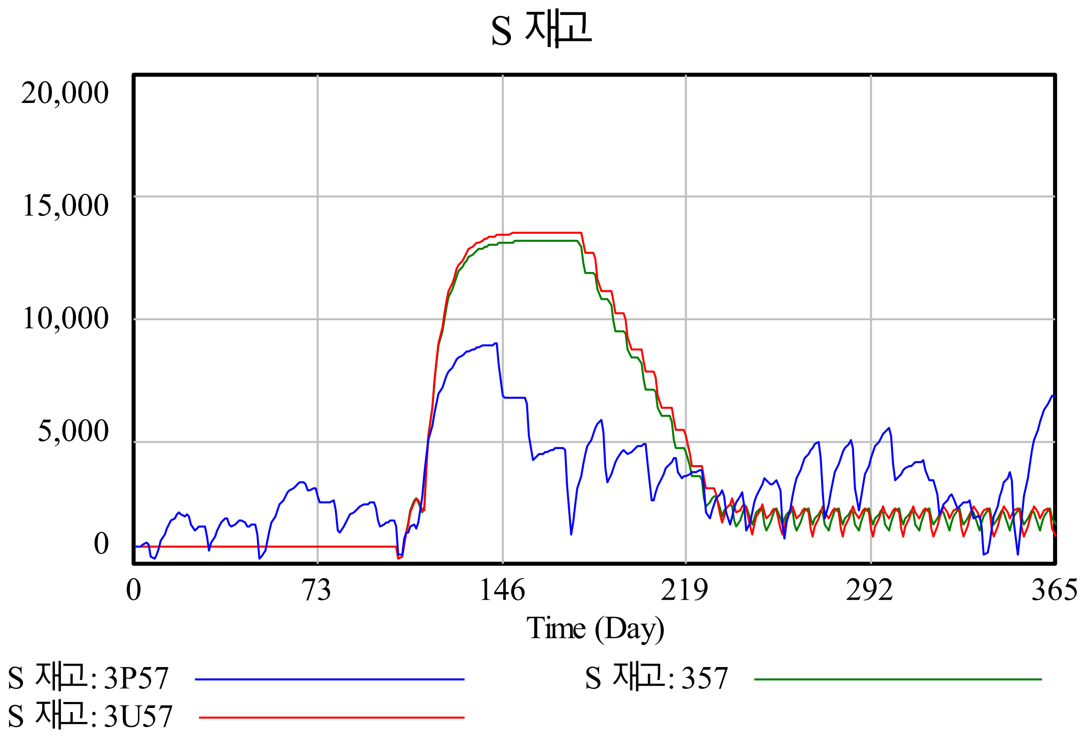
For the 3P57 highlighted in blue, the average stock was 607.77 and the maximum was 1,641. The average or maximum value may vary depending on the seed number. In general, the average increased, and the maximum value that could be called an overshoot decreased.

<Figure 2-12> Change in M inventory when R perceived lead times are generated and applied to target supply lines and target safety days (3P57)



3In the case of P57, it can be seen that the overshoot of M stock has decreased significantly. The average inventory also decreased to 1,776, with a maximum of 5,953.

<Figure 2-13> Change in S inventory when R perceived lead times are generated and applied to target supply lines and target safety days (3P57)



The average of the S stock of the 3P57 was 3,465, lower than the 4,068 of the 357 and the 4,217 of the 3U57. It means that the inventory has decreased. This is because the maximum stock value, the size of the overshoot, has been significantly reduced from 13,209 to 8,989.

As the uncertainty of lead times rises, inventories should increase. Nevertheless, it was confirmed that the amount of S inventory decreased.

Table 2-2< > Impact of Lead Time Volatility on Inventory Volume

model	R Stock Maximum	R Stock Average	M Stock Maximum	M Stock Average	S Stock Maximum	S Stock Average	Total Inventory
3P57	1,642	608	5,954	1,776	8,990	3,466	5,850
357	2,010	539	11,534	2,130	13,210	4,069	6,738

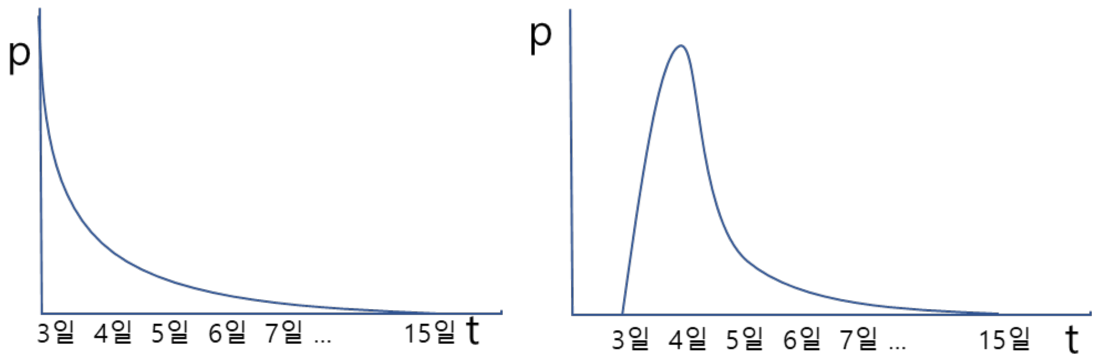
357 is when the lead time is constant stable, and 3P57 is when the lead time is volatile, which is smoothed and reflected in the target supply line and target safety level. It is common sense that if there is uncertainty about lead times, inventory should increase overall. However, it can be

seen that the average of M inventory has decreased, and the average value of S inventory has also decreased, and the total inventory is decreasing. It can be said that our common sense has been broken.

I think it could be a problem with Little's Law. Let's say the value of the stock is 100. It keeps flowing in and filling 100. What flows is simply divided according to Little's Law. Using Random Uniform, values of 2,3,4 are used with the same frequency. When divided by 2, 100/2=50. When 3 is used, 33 goes out. When 4 is applied as the lead time, 25 goes out. The sum of the three exits is 50+33+25=108. If the median value 3 is used 3 times in a row, 33*3=99. Lead time 2 and lead time 4 are equally likely to be used, but the effect of 2 and 4 is twice as different. In other words, the effect when the lead time is short is greater than the effect when the lead time is long. It is analyzed that the amount flowing from M to R has increased due to the overinfluence of the lead time that is lower than average.

In general, the distribution of lead time has a large exponential distribution. A normal distribution is not suitable. The exponential distribution takes the form shown in the following figure. There are many more examples, but just two examples.

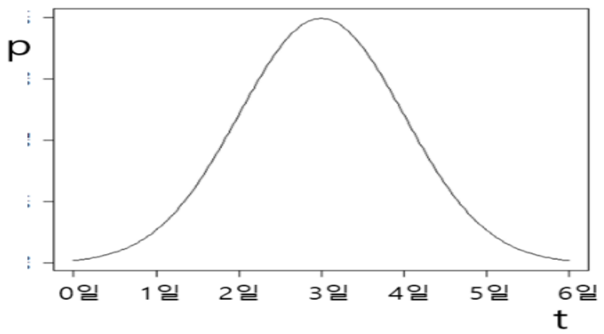
<Figure 2-14> Example of exponential distribution



In the figure on the left in <Figure 2-14>, the probability of 3 days occurring is the largest, the probability of 4 days occurring, and the probability of 5 days getting smaller and smaller. It can even happen up to 15 days, and even bigger lead times. But two days to the left can't happen. Of course, negative numbers cannot also occur. The graph on the right in <Figure 2-14> is similar. It shows that the probability of 4 days is higher than the probability of 3 days. Again, the probability of a negative number or 2 days is zero.

In comparison, an example of a normal distribution is as follows.

<Figure 2-15> Example of Normal Distribution



In a normal distribution, the mean is located in the middle and both sides are symmetrical. And since the ends are open, negative numbers can occur. Because of these characteristics, normal distributions should not be used for arrival times or lead times. There may be cases where it is a normal distribution and limits the minimum and maximum values.

Finally, when lead time variability is expressed for S, M, and R, we look at how the total inventory varies.

To this end, part of the previous model was modified as follows.

M LEAD TIME = RANDOM UNIFORM(2.5, 7.5, 1234)

M Perceived Lead Time = SMOOTH(M Lead Time, 5)

M Target Supply Line = M Perceived Lead Time*M Prediction of Consumption

M Safety Level Days = M Perceived Lead Time

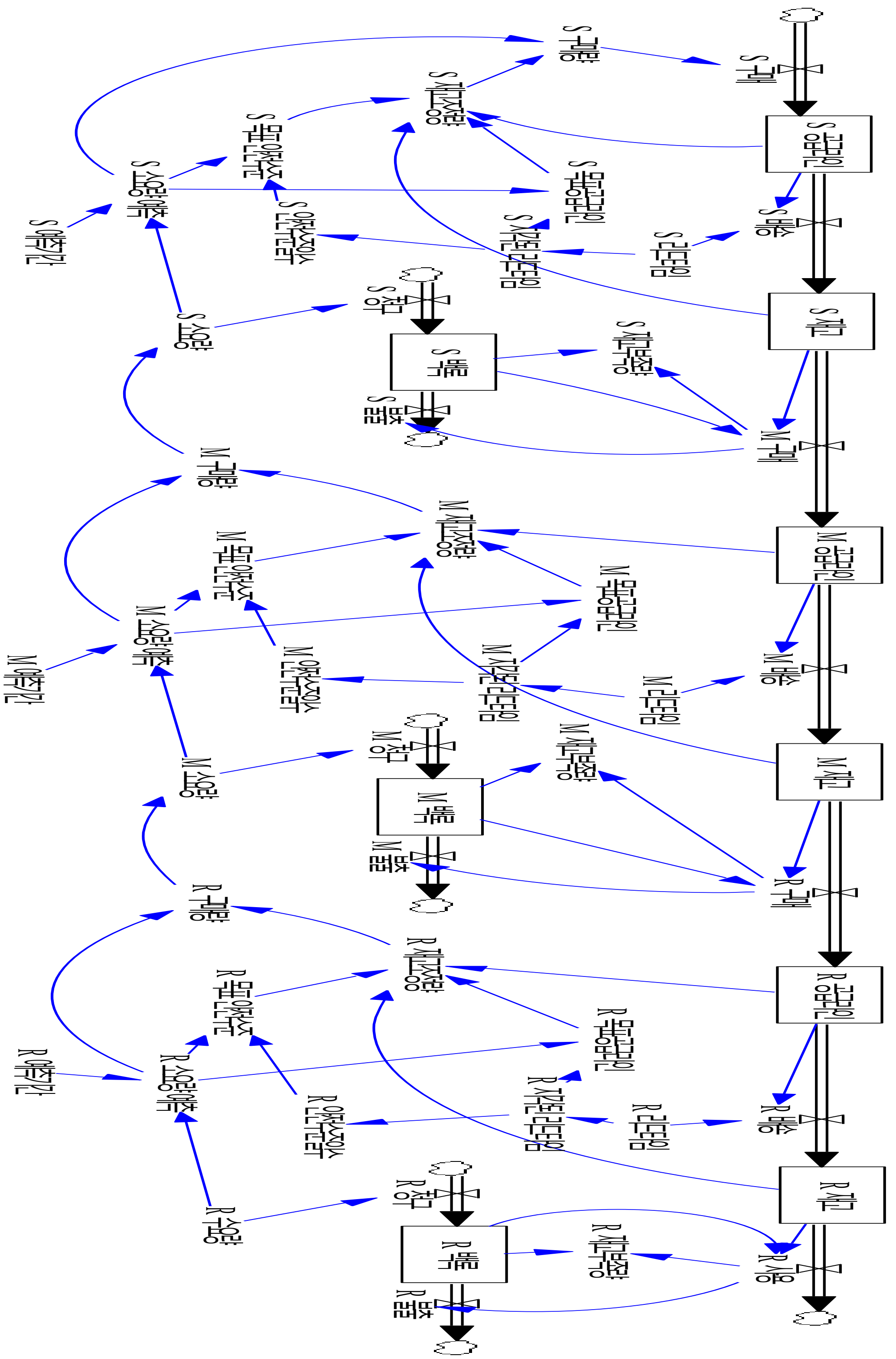
S LEAD TIME = RANDOM UNIFORM(3.5, 10.5, 1234)

S Perceived lead time = SMOOTH(S lead time, 7)

S Target Supply Line = S Perceived Lead Time*S Prediction of Consumption

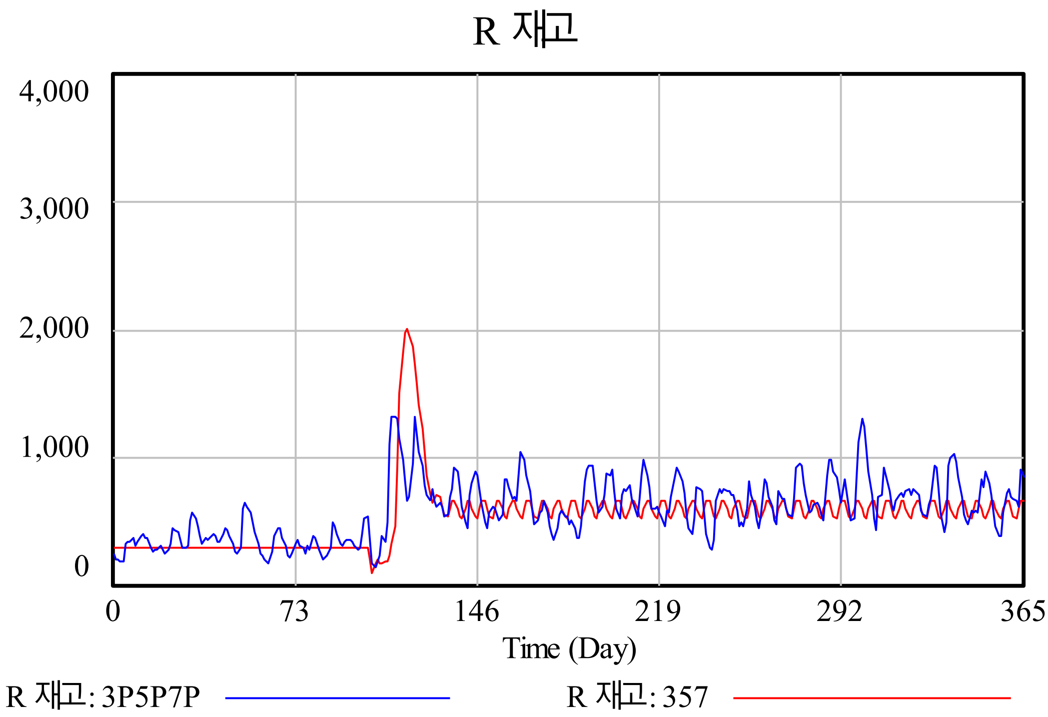
S safety level days = S perceived lead time

<2-16> Modified Models



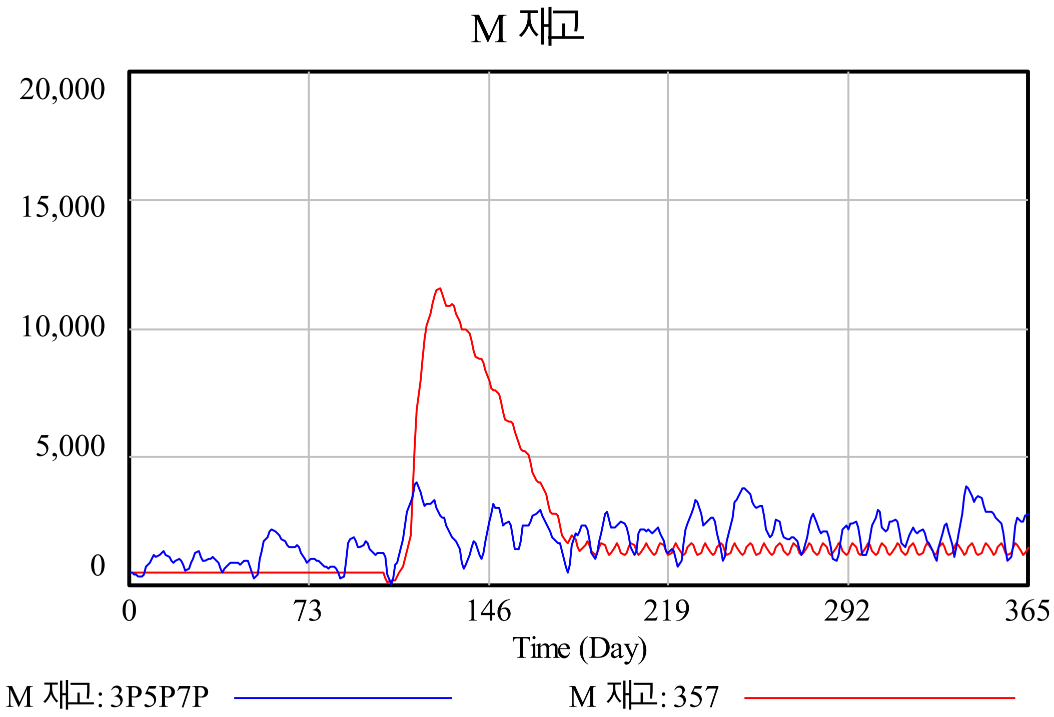
Then, a vensim data file called 3P5P7P was generated and simulations were performed.

<Figure 2-17> R Rethinking When Lead Time Uncertainty Manifests Uncertainty for Everyone



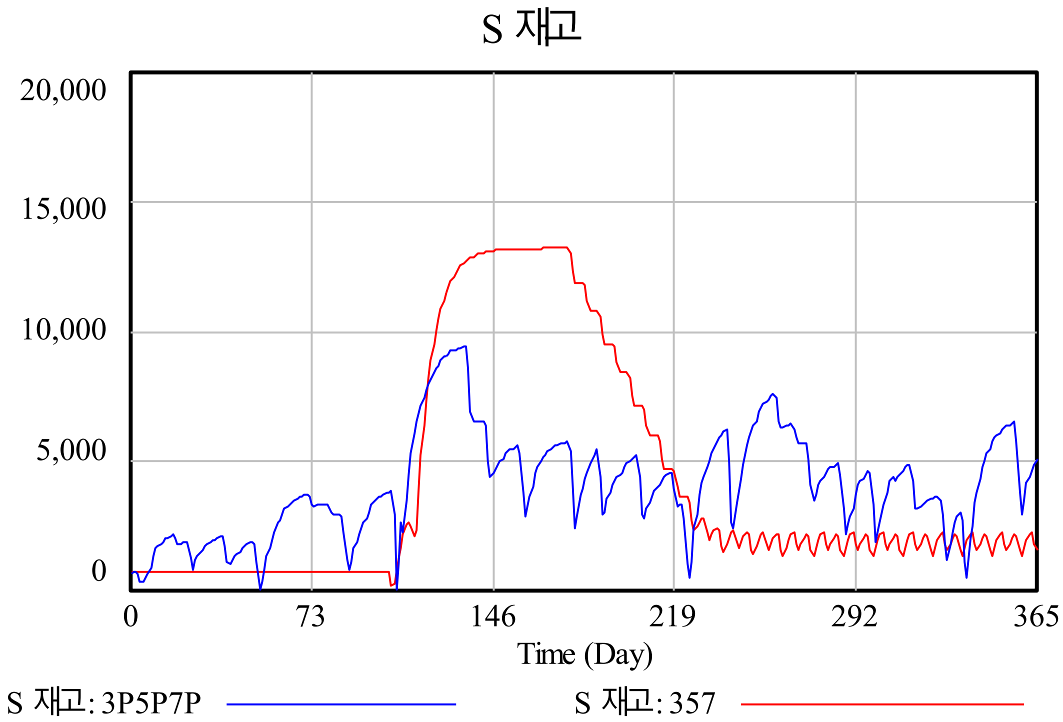
3Compared to 57 (lead time is constant), the maximum value is smaller, but the deviation when there is a small uncertainty is large. The average R inventory for 3P5P7P was 593.84, up from 538.84 at 357. The maximum value was reduced to 1,323.

<Figure 2-18> M Rethinking Lead Time Uncertainty for Everyone



3Compared to 57 (2,130, 11,533), the average value of 3P5P7P decreased to 1,846 and the maximum value to 4,011. It is believed that the impact of overshoot due to great uncertainty is great. Looking at the change after 220 days without significant changes, 3P5P7P is greater than 357.

<Figure 2-18> M Rethinking Lead Time Uncertainty for Everyone



When the uncertainty of lead times was exposed to all participants in the supply chain, S inventory actually decreased. The average was 4,030 compared to 4,068 in 357, and the maximum value was also reduced from 13,209 to 9,392.

<Table 2-3> Impact of Lead Time Uncertainty on Supply Chain Inventories

	R Stock	M Stock	S Stock	Full stock
357	539	2,130	4,068	6,737
3P57(R만)	608	1,776	3,465	5,849
3P5P7P (all SMRs)	594	1,846	4,030	6,470

Since the simulation was performed on only one seed, it should not be generalized. Nonetheless, it is clear that lead time uncertainty is not only a negative impact on the supply chain . The fact that inventories are the highest in the absence of any lead time uncertainty provides significant significance. It seems perfectly reasonable that more inventory occurs when exposed to uncertainty as a whole than when exposed to uncertainty in part.

Chapter 3

The impact of forecast accuracy on the supply chain

Forecasting Accuracy on the Supply Chain

Demand arises independently. Inventory is held to maintain constant service in response to uncertain demand. That is, inventory is determined by deviations in demand. Reflecting these characteristics, the periodic inventory system sets a target inventory (target: T) and orders the target inventory minus the current inventory when the replenishment cycle occurs. Here, the target inventory determines the overall inventory level.

$$T = \mu \times (p + lt) + z \times \sigma \times \sqrt{(p + lt)}$$

Here , each sign means:

μ: *수요의 평균*

P: Cycle of order

lt: Lead time

z: Value in a normal distribution standardized to the service policy index

Target inventory includes the mean and standard deviation of demand. Recently, however, the development of AI technology and various algorithms has been booming. These techniques are being used to make predictions more accurate. There are increasing reports that the previous 50% accuracy has improved to 90% with the new algorithm. With this improvement in forecasting accuracy, of course, inventory should be reduced. However, there is no room for forecast accuracy in the target inventory formula mentioned above. Therefore, the improvement of prediction accuracy is nothing more than an empty fire.

This is not unique to periodic inventory systems. The same phenomenon occurs in the continuous inventory model (the so-called Q system). The reorder point formula in the Q system is as follows.

$$ROP = \mu \times lt + z \times \sigma \times \sqrt{lt}$$

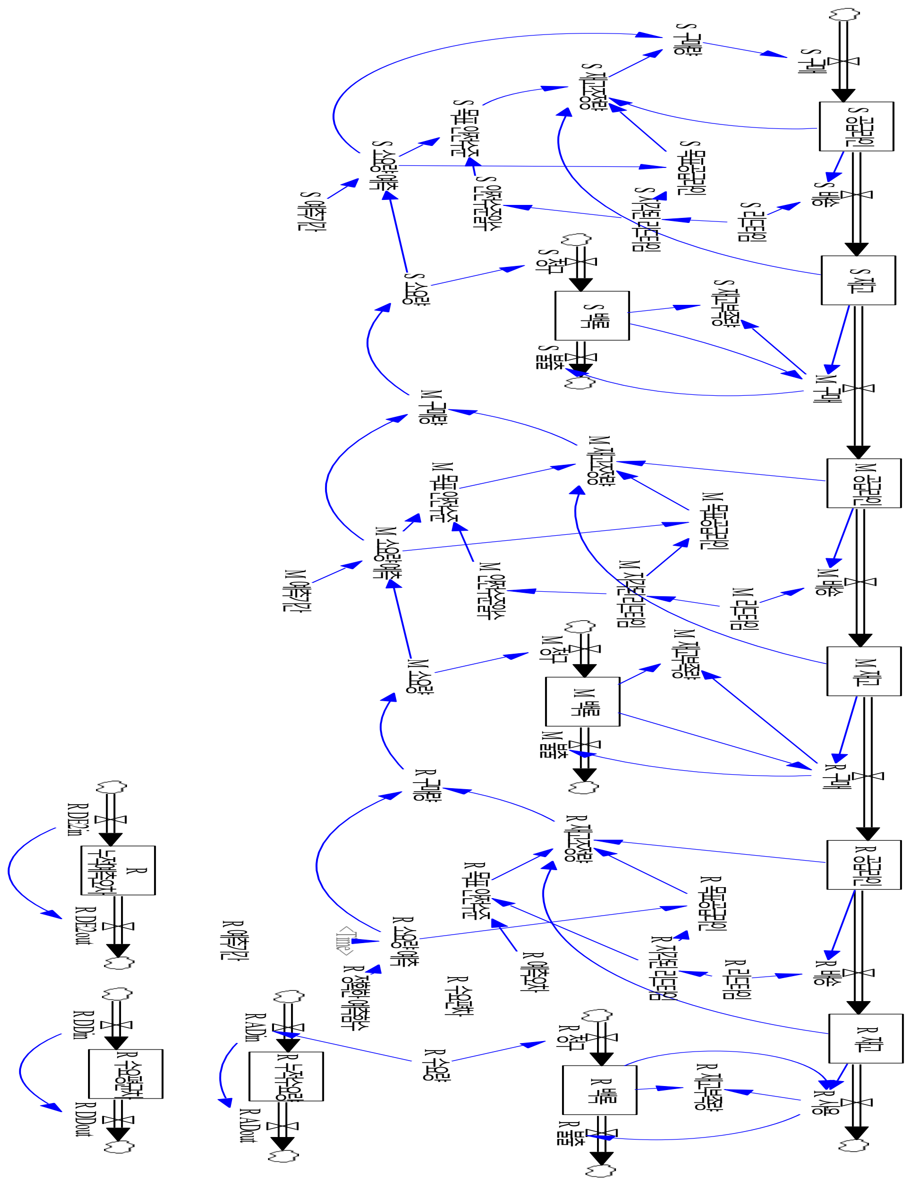
In the Q system, ROP contains safety stocks and determines overall inventory levels. Here, too, deviations in demand are used, and forecast accuracy is not reflected.

It has been argued that the forecast error should be used instead of the deviation of demand to reflect the prediction accuracy (Zinn and Marmorstein, 1990, Nguyen et al., 2010, Mizaee, 2017, Seyedan and Makakheri, 2020, Felberbauer et al., 2021). The authors strongly agree. In this chapter, we'll create a somewhat far-fetched model to see how forecast accuracy affects supply chain inventory.

1) Build a supply chain model to reflect prediction accuracy

<The R portion of the model in Figure 1-1> was modified. This is because a module is needed to measure the standard deviation and forecast error of demand. The finished model is shown in the following <Figure 3-1>.

<Figure 3-1> Model to determine the impact of forecast accuracy on supply chain inventories



The formula used in the R part is as follows:

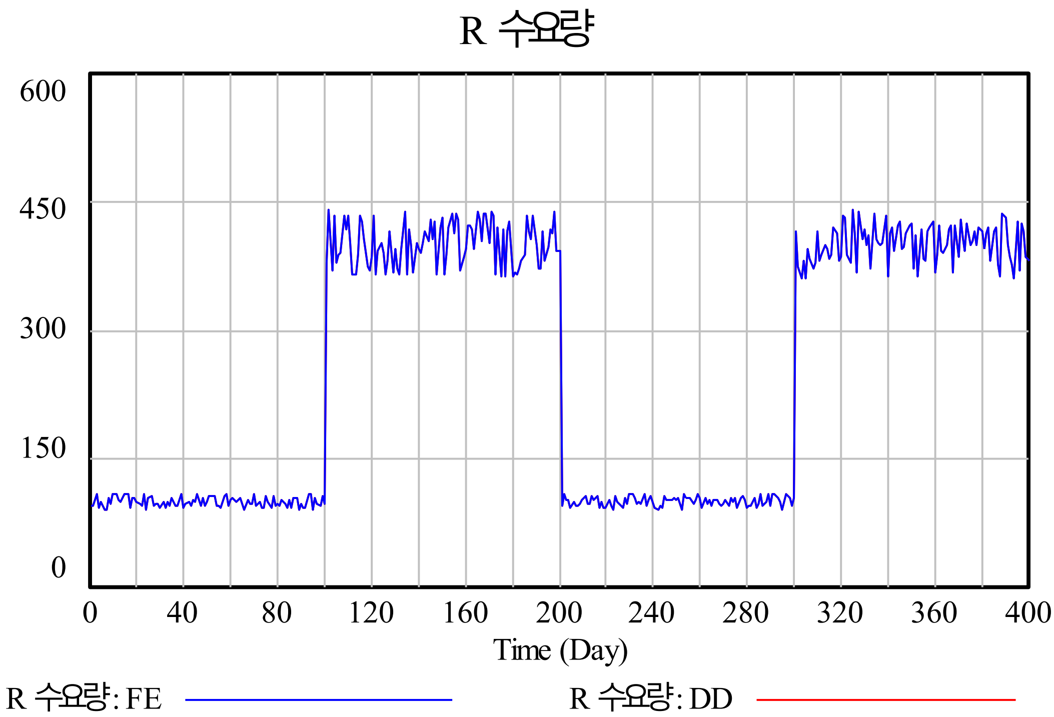
Table < 3-1> Prediction Accuracy-Formula for R Parts Used in Inventory Model

R target safety level=2*R predicted error*POWER(R perceived lead time, 0.5)
R ADin= R Demand
R requirement prediction = R accurate prediction function (Time)
R DDin=POWER(R demand-R cumulative demand/R forecast period, 2)
R demand deviation=SQRT(MAX(0, R demand mean difference/R prediction period))
R DE2out=DELAY FIXED(R DE2in, R prediction period, 0)

```
R prediction error = SQRT( MAX(0, R cumulative prediction error/R prediction period))
R cumulative demand = INTEG (   R ADin-R ADout,R forecast period*100)
R cumulative prediction error = INTEG (R    DE2in-R DE2out,0)
R Demand mean difference = INTEG (R DDin-R DDout,0)
R DE2in=POWER(R demand-R requirement forecast, 2)
R DDout=DELAY FIXED(   R DDin, R prediction period, 0)
R ADout=DELAY FIXED(R ADin, R 예측기간, 100)
R exact prediction function([(0,0)-(400,400)],(0,100),(100,100),(101,400),(200,400),(201,100),(300,100), (301,400), (400,400))
R Perceived Lead Time=SMOOTH(R Lead Time, 3)
R Target Supply Line = R  Predict Requirement*R Perceived lead time
R LEAD TIME=RANDOM UNIFORM( 1.5, 4.5, 1234)
R Supply Line = INTEG (R Purchase-R Delivery, R Target Supply Line)
R Inventory Adjustment Amount=R Target Safety Level-R Inventory+R Target Supply Line-R Supply Line
R BUY=  MIN(M Stock, M Backrock)
R purchase volume = MAX(0, R requirement forecast + R inventory adjustment)
R Shipping=       R Supply Line/R Lead Time
R backrock= INTEG (R      claim-R dismissed,100)
R dismissed=      Use R
Use R=  MIN(R backrock, R stock)
R 수요량=(100+300*PULSE TRAIN( 101, 100, 200, 400))*RANDOM UNIFORM( 0.9, 1.1, 3456)
R prediction period=3
R Inventory = INTEG (R    Shipping-R Enabled, R Target Safety Level)
R Outstock=MAX(0, using R backrock-R)
R Charge=         R Demand
```

To create a slightly dramatic situation, the R demand amount was arbitrarily made. (100+300*PULSE TRAIN(101, 100, 200, 400))*RANDOM UNIFORM(0.9, 1.1, 3456), which shows the following <Figures 3-2>

<Figure 3-2> R Demand Change



Using the PULSE TRAIN function and the RANDOM UNIFORM function, an average of 100 demands occur for 100 days, and an average of 400 demands occur continuously for the next 100 days, and a total of 401 days of repeated occurrence. It would be good to understand it as something like clothes that sell well in spring and autumn. Since it is multiplied by a value between 0.9 and 1.1 in an even distribution, there is a maximum uncertainty of 10 down and up for 100 in the off-season. During the peak season, it is around 400 and 10% each, so it fluctuates up and down about 40.

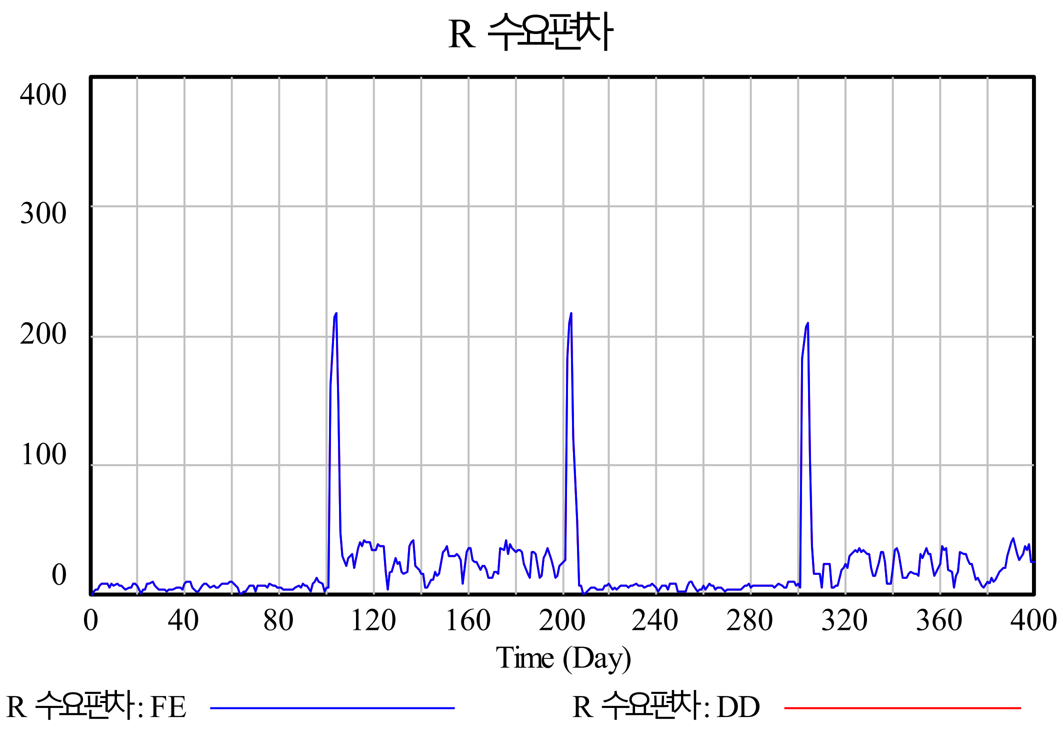
Here, assuming that the predictions for the off-season and peak season are accurate, we created and included a function. The relation of the R exact prediction function was used using the LOOKUP function to look like a smooth PULSE TRAIN function except for the bumpy one in the graph in <Figure 3-2>.

<Figure 3-1> in the lower right section shows the relation for finding the standard deviation of demand and the predicted error (here Mean Squared Error (MSE)). Most of the arrows are hidden to avoid complexity. The reason for creating such a complex formula for finding the prediction error and the standard deviation of demand is that R must obtain information that makes decisions about the two parameters. We who create the model can specify the two parameters, but since party R is not omniscient, we must collect and obtain data. In this process, it was assumed that the cumulative error and cumulative deviation are only found for the past 3 days. Of course,

3 days here is taking into account the R lead time.

<As shown in Figures 3-2>, the standard deviation of demand is shown in the following <Figure 3-3> shown.

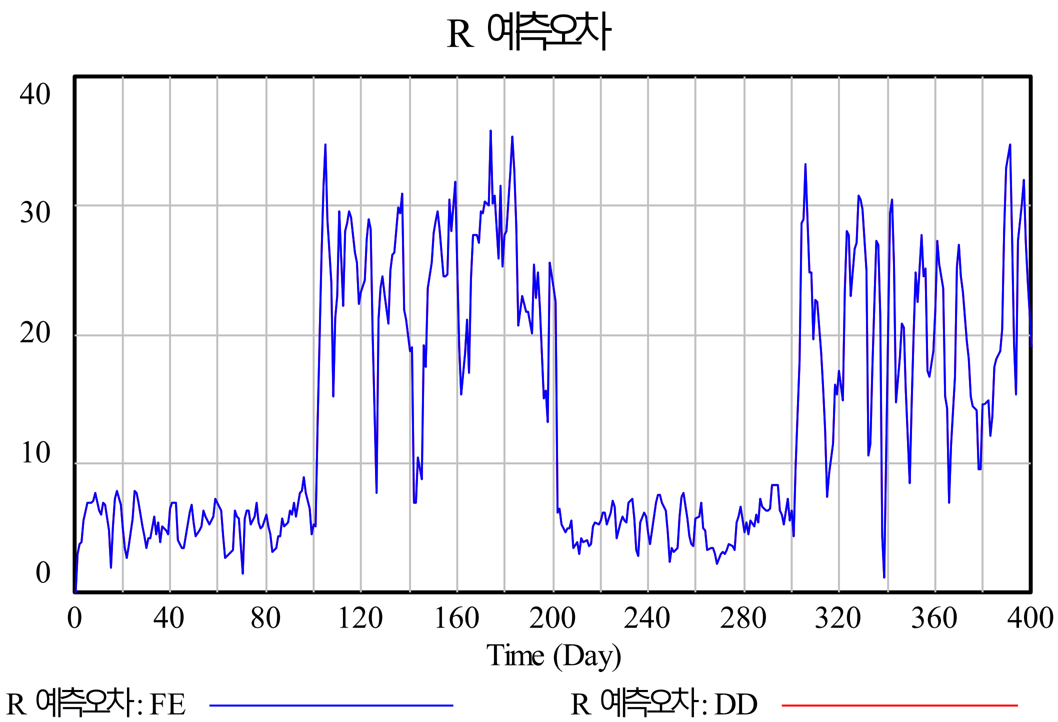
<Figure 3-3> Deviation of R demand



At a time when demand changes rapidly, demand deviations occur temporarily and significantly. The mean of the R demand deviation was 20.16 and the standard deviation was 31.32.

The R prediction error is shown in the following figure.

<Figure 3-4> R Prediction Error



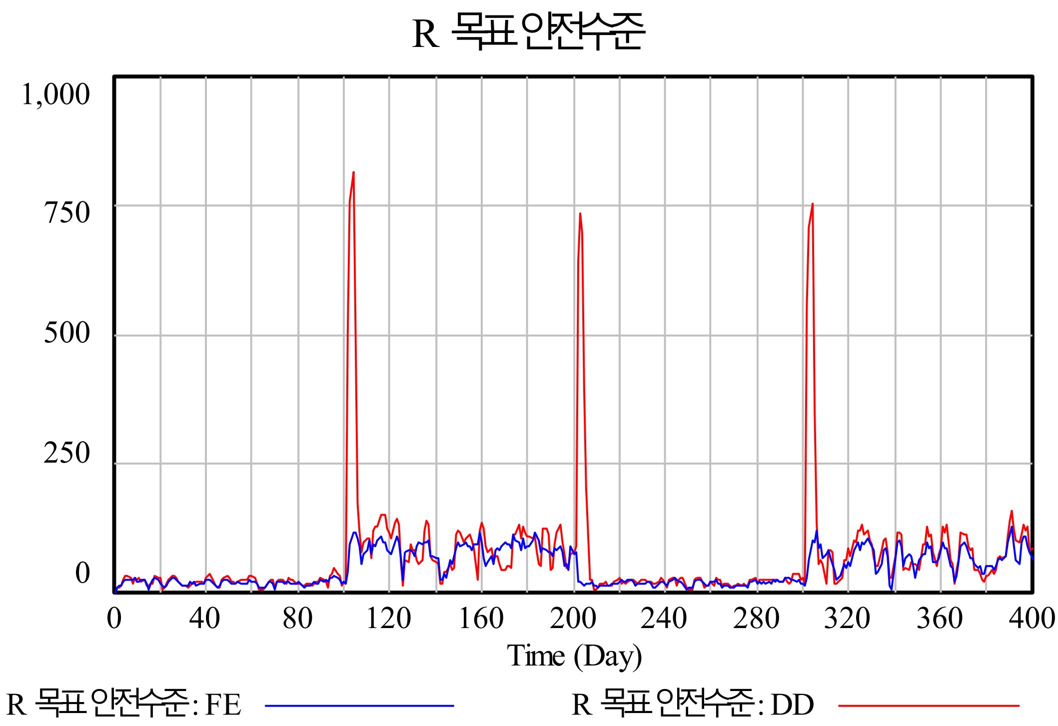
The mean R prediction error is 13.70 and the standard deviation is 9.825. Since the accurate prediction function is used, the value is smaller than the demand deviation.

One of the major differences between the <Figure 3-1> model <compared to the Drawing 1-1> model is the R target safety level.

R target safety level=2*R predicted error*POWER(R perceived lead time, 0.5)

When the R prediction error was included in the right side of the formula, the VDF name was set to FE, and when the R demand deviation was used, it was set to DD. The R target safety level in these two situations is shown in the following figure. Of course, this formula is an application of the safe stock level formula of the continuous inventory model.

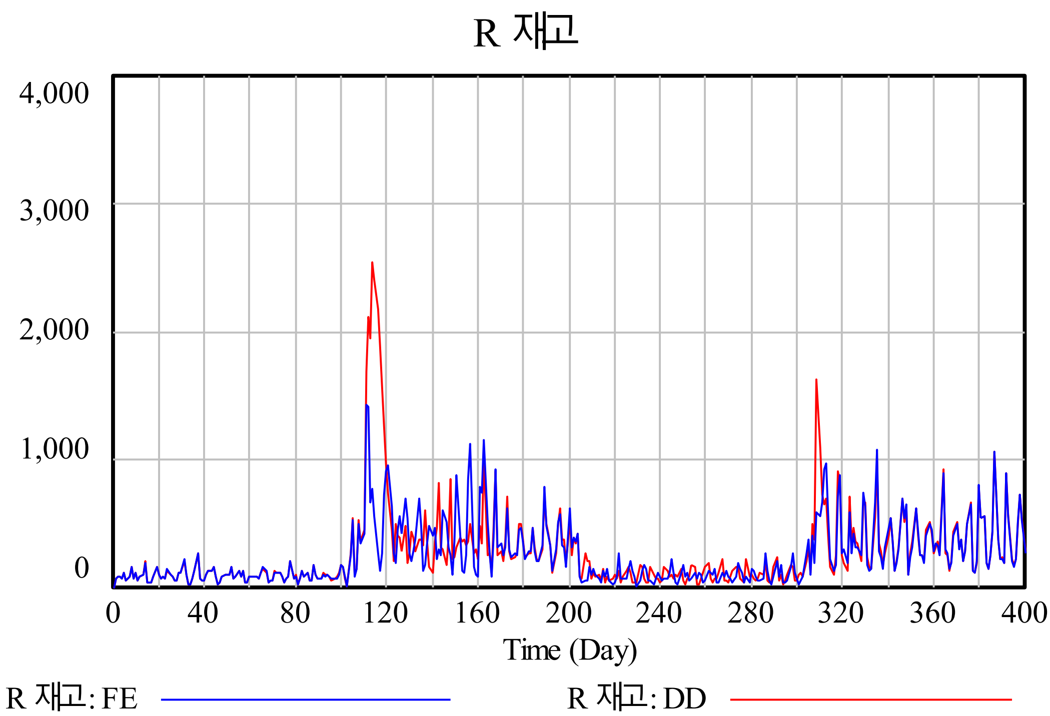
<Figure 3-5> R Target Safety Level



Blue indicates when the forecast error is used, and red indicates when the deviation in demand is used. The peculiarity is that when demand changes rapidly, it is predicted through an accurate prediction function, so the forecast error follows the pattern of demand as it is, but the demand deviation shows a sharp increase at the time of change. Moreover, due to the use of MSE (Mean Squared Error), a temporary but large increase is seen. In the case of DD, it can be expected that the sudden increase in the amount of storage will lead to a temporary increase in the purchase volume, which will lead to a whiplash effect in the supply chain.

In the case of R purchase volume, the average FE (when using forecast error) is 246.61, and DD (when using demand deviation) is 247.77, so there is not much difference.

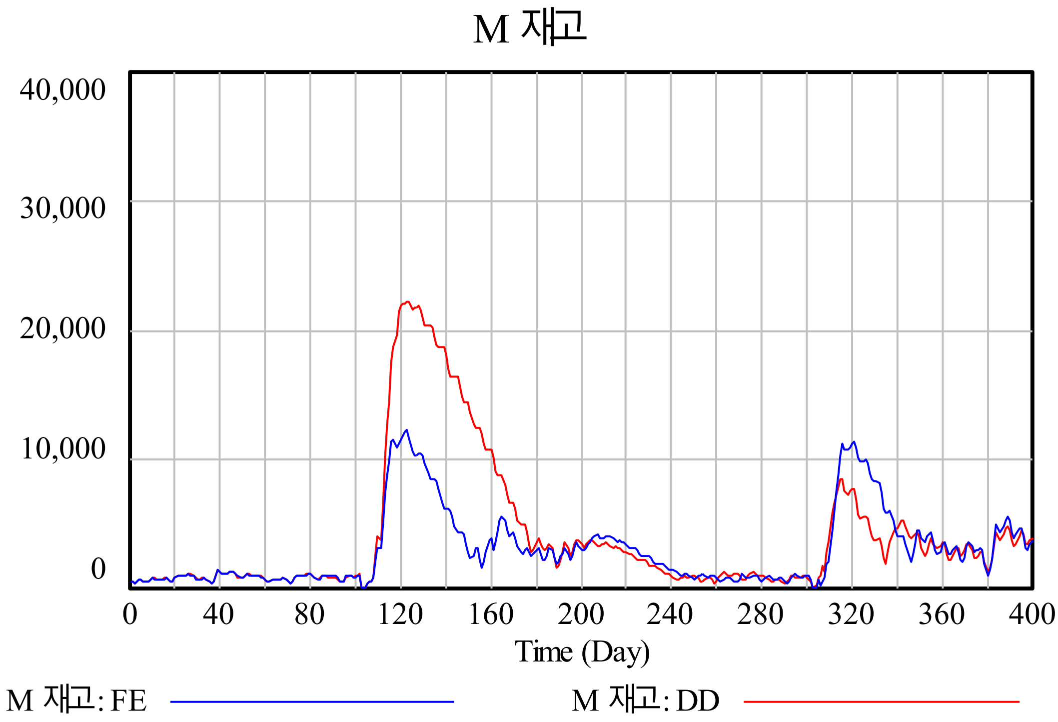
<Figure 3-6> Changes in R Inventory



DD can be seen as inventory surges and then drops rapidly as it moves from off-season to peak season. DD's maximum inventory is 2,535 units. Around 200 days, the demand deviation was high , but inventories did not soar high. This is because when demand changes from a large season to a small season, there is no need to place large orders. R purchases did not show a large order volume around 200 days. The average R inventory was around 250 for FE and 277 for DD. That's about 10% difference.

M inventory, located in the middle of the supply chain , is shown in the following figure.

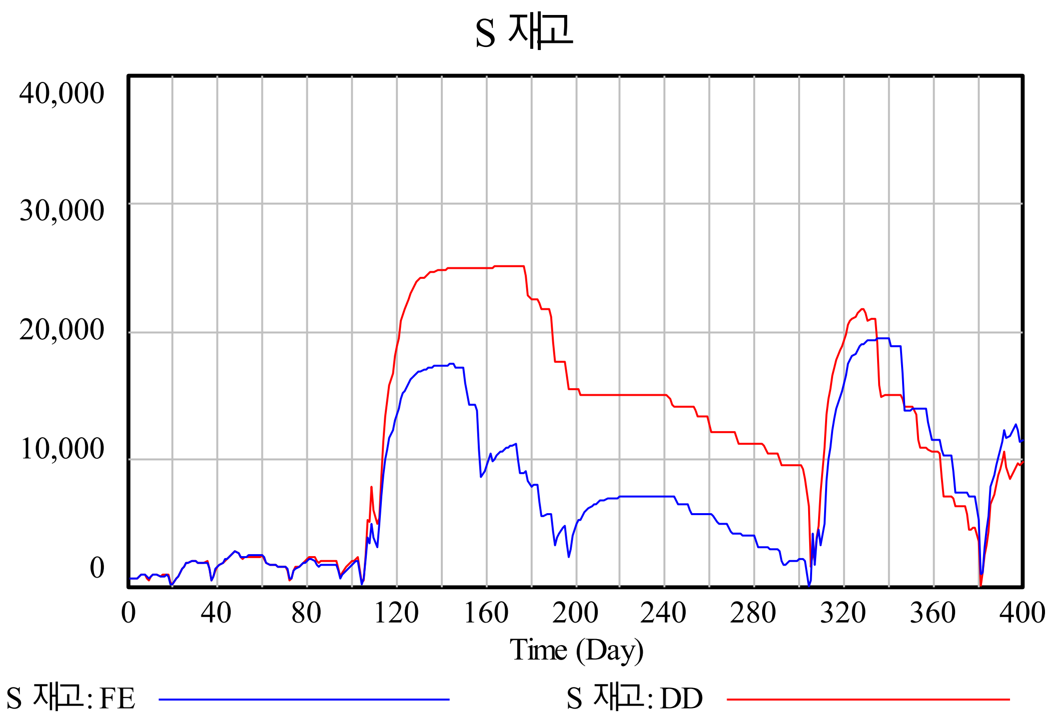
<Figure 3-7> M Inventory Comparison



It can be confirmed that the overshoot of DD has occurred significantly. DD's M inventory has a maximum overshoot of 22,260, which is only half the FE's 12,214. Accordingly, the average M inventory is 3,026 FE and 4,117 DD. It's a big difference.

S inventory appears as shown in the following figure.

<Figure 3-8> S Inventory Comparison



In the case of S inventory, the average of the DD is 11,589 compared to the FE average of 7,297. represents an increase of about 59%. Looking at the overshoot, DD appears higher and longer. The overshoot continues during the peak season, which ranges from 201 to 300 days. It can be seen that the early whip effect has been seen in DD's S stock for a very long time.

Improving forecast accuracy should be reflected in inventory policy. As described in this chapter, it is possible to use the forecast error instead of the demand deviation. Using forecast error instead of demand deviation can lead to a decrease in inventory levels. In particular, it was analyzed because it generates less whiplash effects. It is necessary to generalize by simulating more seeds. The results of this study on one seed cannot be generalized.

Table 3-1< > Comparison of Forecast Error and Demand Deviation in Supply Chain

	R Stock	M Stock	S Stock	Full stock	comparison
FE (Prediction Error)	250.04 1,421	3,026 12,214	7,297 19,495	10,573 3,130	Inventory:51 % reduction
DD (demand	277.40	4,117	11,589	15,983	Maximum

deviation)	2,535	22,260	25,041	49,836	value: 50% reduction

In terms of inventory, R inventory did not change much. At a time when demand was rapidly changing, inventory adjustments occurred significantly, and DD experienced a flood of orders in some segments. R The difference in inventory is only 10%. However, this temporary rush of orders is a big burden for M. Overall, M inventory and S inventory are greatly affected by R purchase volume, resulting in a 50% difference in inventory overall.

The reason we continue to suggest the maximum value is that when inventory is stored in a warehouse, the maximum value affects storage capacity. The maximum value of each warehouse shown in Table 3-1> < represents the size of the warehouse that each warehouse should have. It shows that when using deviations in demand, 50% more warehouses should be secured than when using forecast errors. If we consider these costs, it can be said that just changing one parameter means a lot.

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Chapter 4

Information sharing in the supply chain

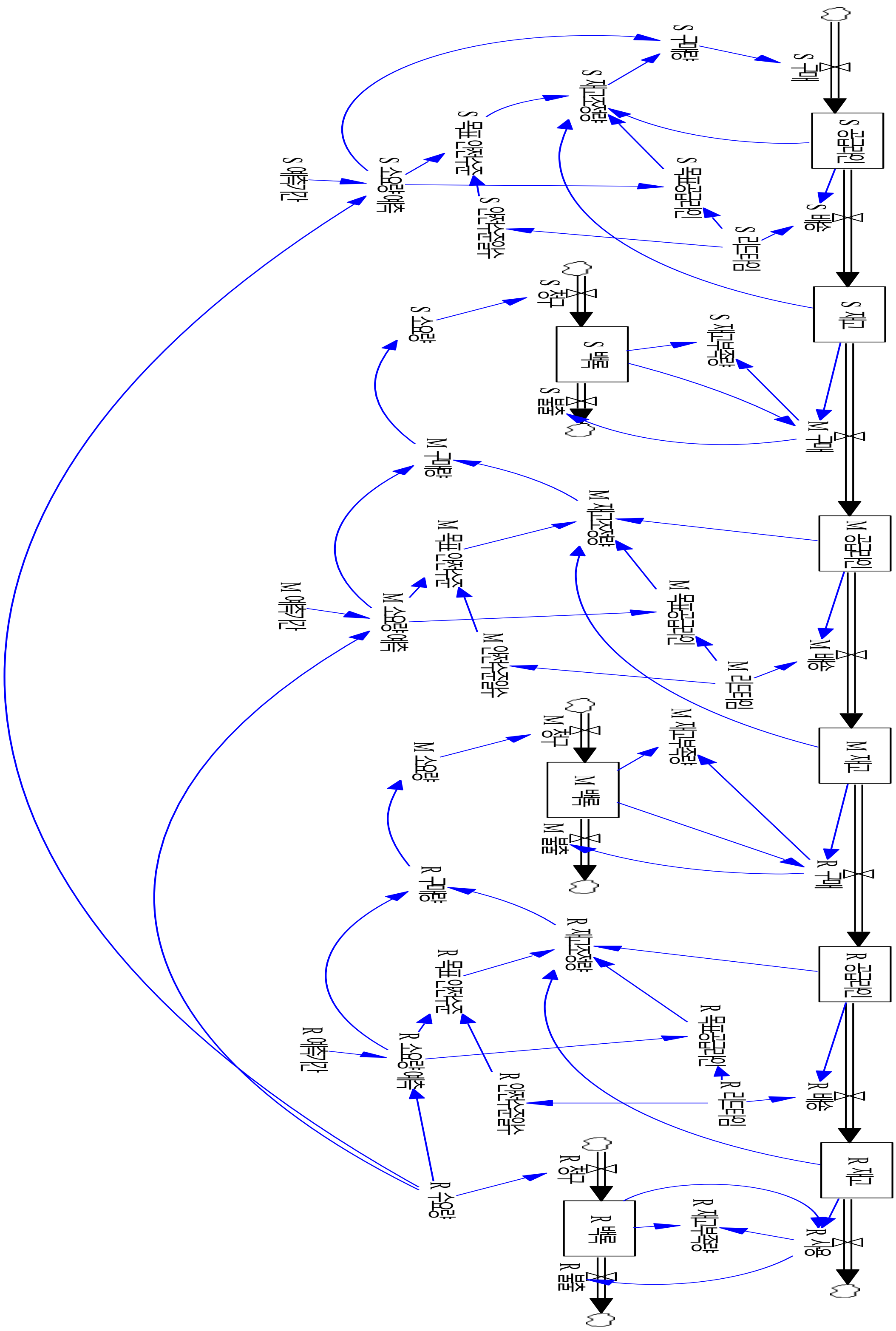
Information Sharing on the Supply Chain

The information shared between supply chain participants is diverse, including demand information, inventory information, transportation status information , price information, and promotional plans. Among them, the most important thing is the sharing of demand information. If the participant at the lowest level delivers the information at the point of sale (POS) without filtering it upstream, the response ability of the upstream participant is improved. But we need to see how much it will improve.

1) Inventory reduction due to demand information sharing

In this chapter, the model used in <Figure 1-1> is taken and only the information sharing part is modified. At the bottom of <Figure 4-1> you will notice two long arrows. Let's see what effect occurs when M and S accept R demand as it is.

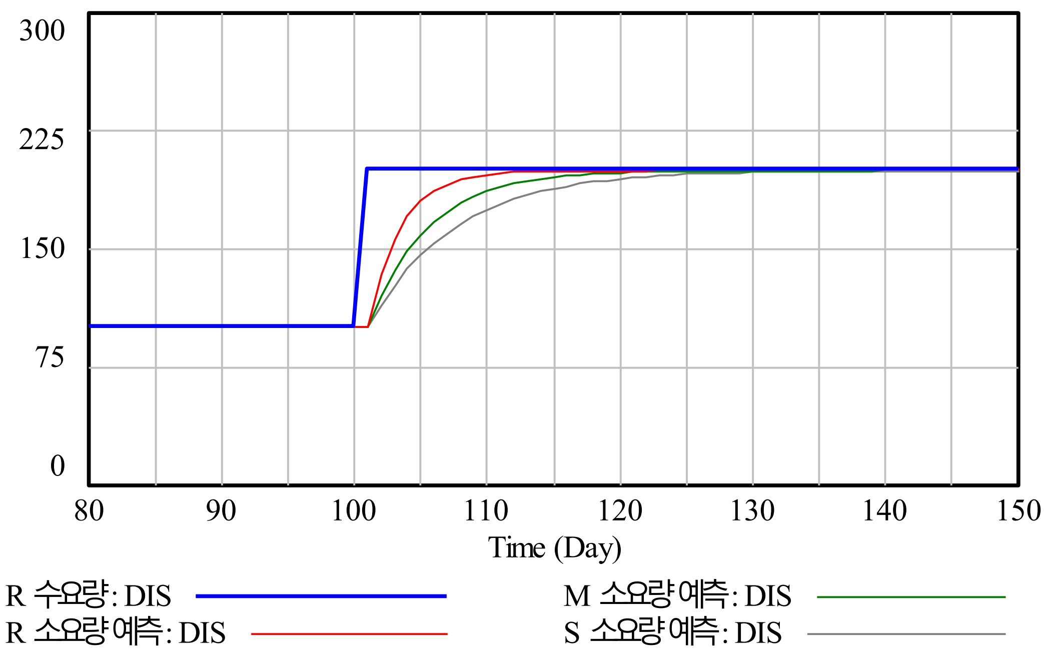
<Figure 4-1> Three-step supply chain model for sharing demand information



The lead time of M and S is different from the lead time of R. 5 days and 7 days, respectively. Accordingly, the forecast period for M and S is also 5 and 7 days. Even if the R demand is accepted as it is, the M requirement forecast and the S requirement forecast show a difference. The required forecast is a component of the target supply line and the target safety level. Therefore, this forecast is very important for inventory management. Changes also occur from the M perspective. It changed from predicting based on R purchase volume to R demand volume. The existing simulation file name was 357, and the case where demand information was shared was named DIS.

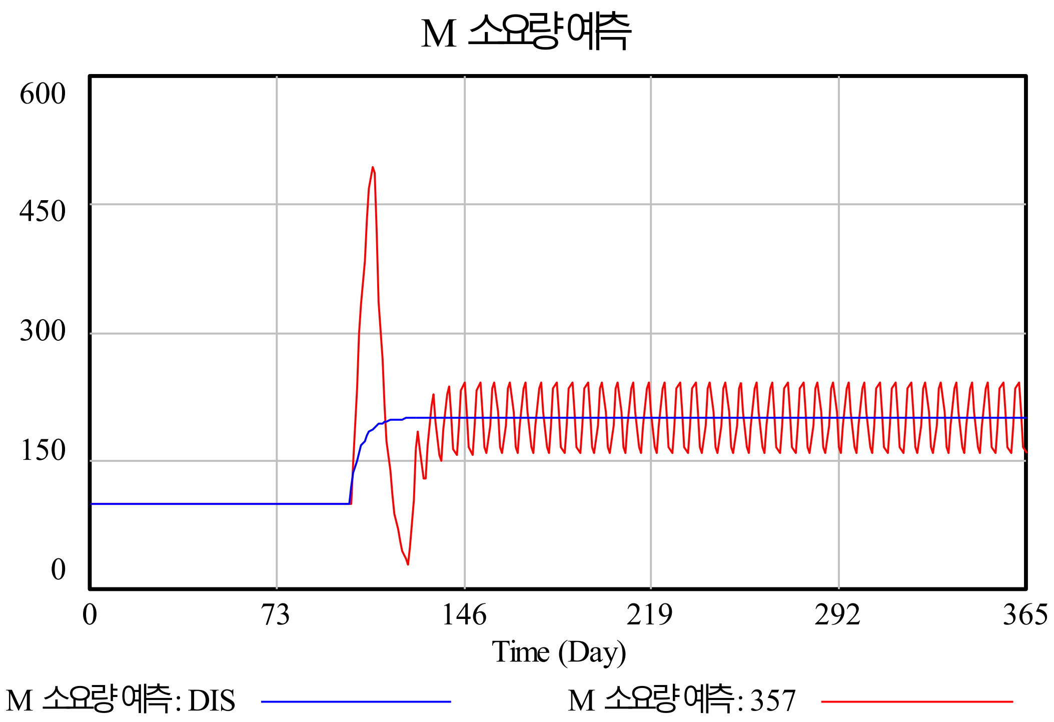
For reference, the R demand is expressed as a thick line in the following <Figure 4-2>.

<Figure 4-2> Forecasting R demand and S, M, and R requirements



The fastest approaching quantity of demand is R, followed by M and S. This is an enlarged picture of between 80 and 150 days out of 0 to 365 days. This is because the smoothing period has been increased to 3, 5, and 7 based on the same amount of demand. M Estimates are also looked at when demand information is shared and when it is not.

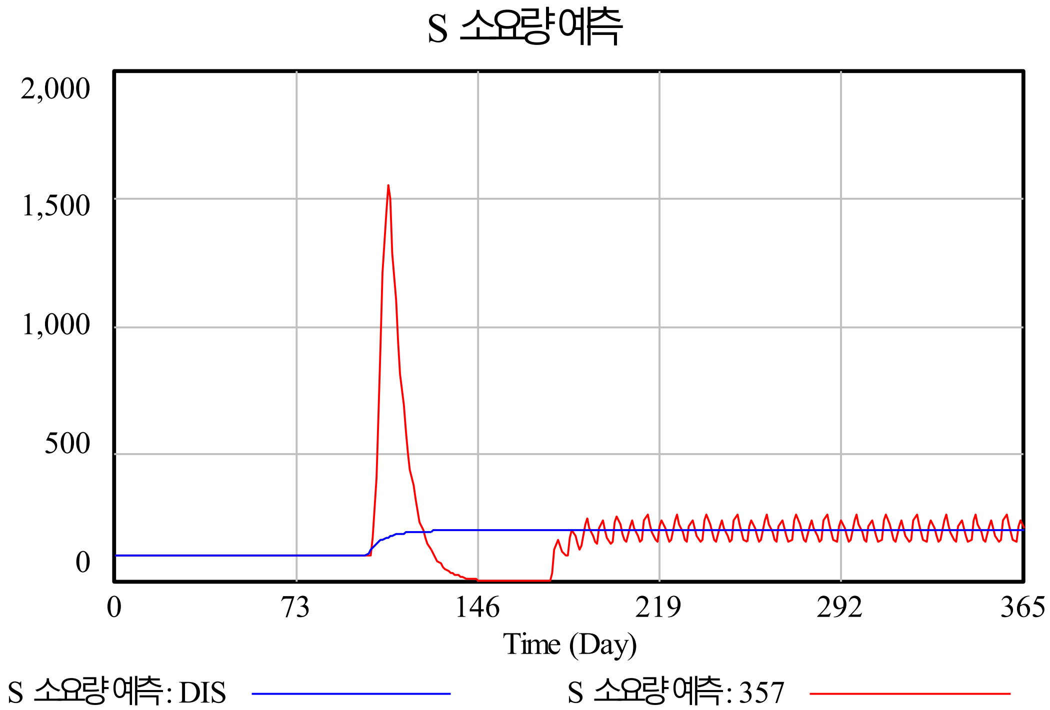
<Figure 4-3>　Estimation of M requirements for information sharing and non-sharing



This is the case when the line with large fluctuations is not shared information.　There is a distinct difference.　Without information sharing (357), the mean of M requirement predictions is 172.58 with a standard deviation of 66.13.　In comparison, the mean for information sharing (DIS) is 171.03 and the standard deviation is 44.68.　The means are almost similar, but there is a large difference in standard deviation.

If we compare the S requirement predictions, the difference between the two patterns is greater.

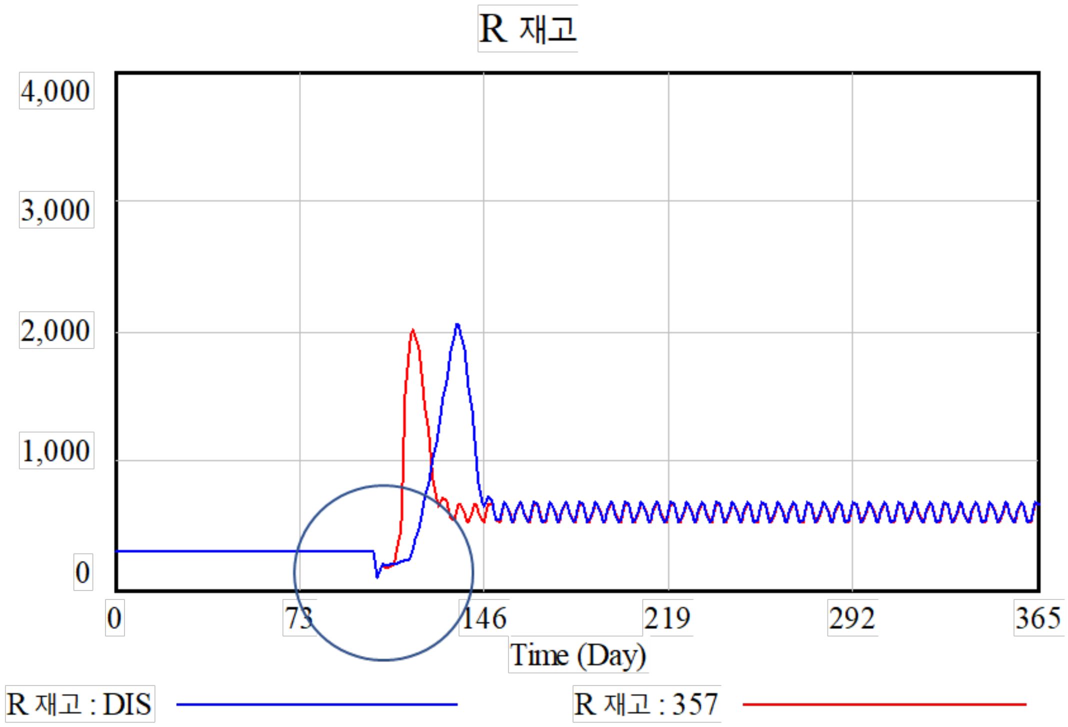
<Figure 4-4>　S Estimate of Information Sharing and Non-Sharing



Supply chains that do not share demand information may exceed 1,500 S requirements.　Zero may persist for a while.　The mean and standard deviations of the 357 model are 176.04 and 189.98, and the DIS model is 170.49 and 44.62.　This standard deviation is less than the standard deviation of M.

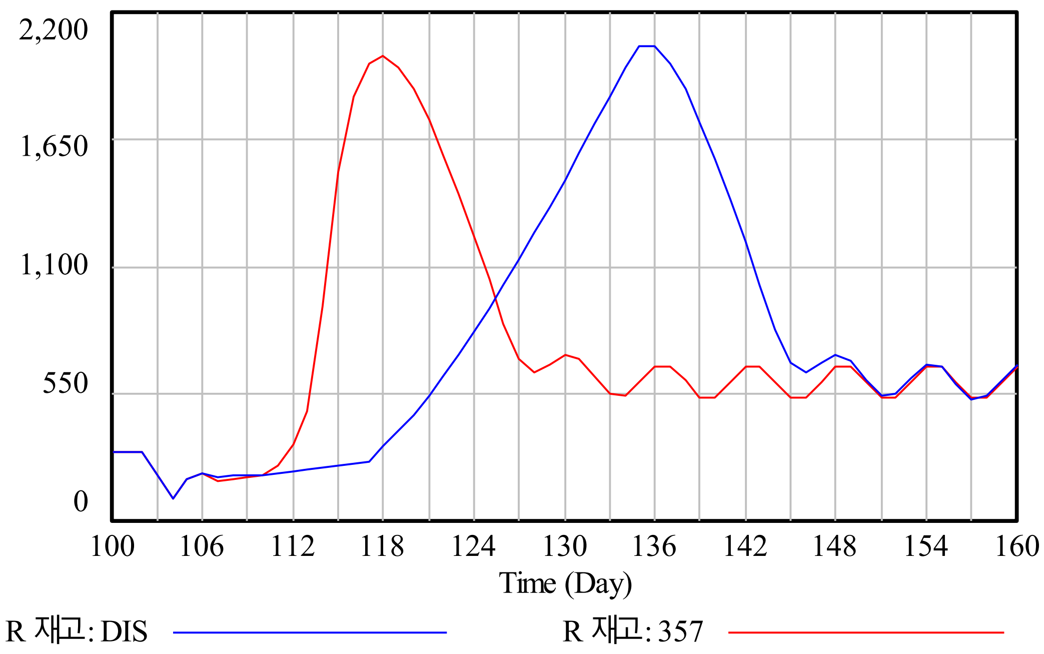
The effects of information sharing are examined in terms of inventory.　R inventory did not show a significant effect of information sharing.

<Figure 4-5> R inventory comparison according to information sharing



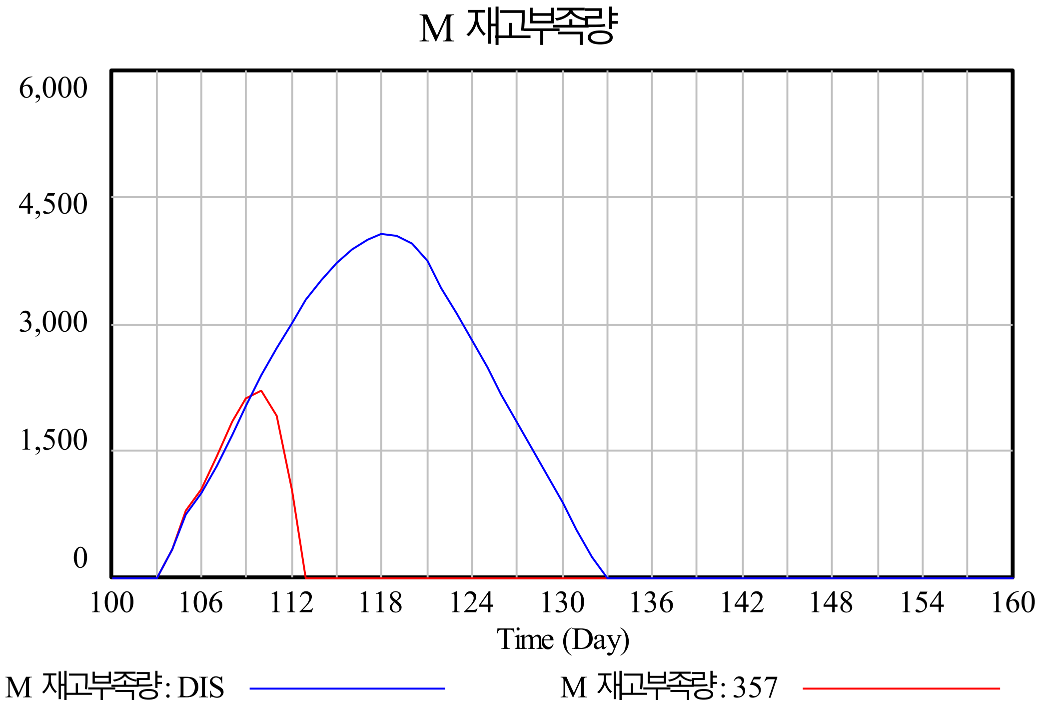
In terms of R inventory, the DIS was 548.76 and the 357 model was 538.84. The standard deviation was also larger, at 289.40 and 254.22. Information sharing means that for R at the bottom of the supply chain, inventory will increase, and uncertainty about inventory will increase. If the information was provided faster and without noise, the results could be worse. We need to see why this happens. <If you look at the circled part in Figure 4-5>, the blue line is the diss. You can see that the blue line recovers later than the red line.

<Figure 4-6> Graph enlarged from <Figure 4-5>



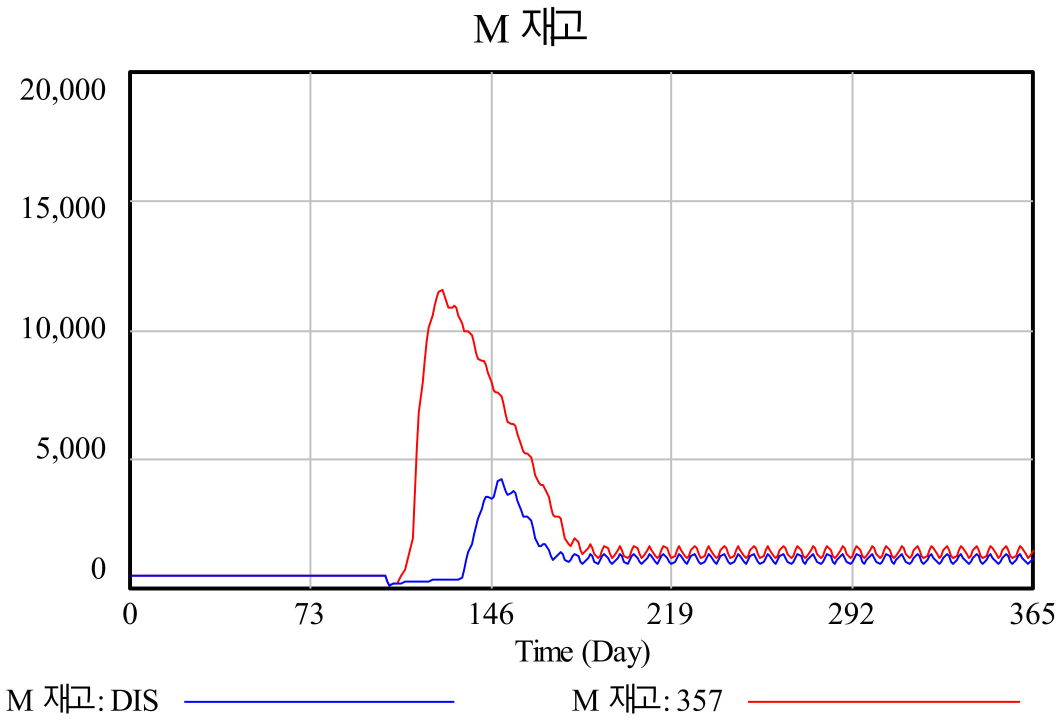
Between 106 and 120 days, the blue line is rising late. I have never modified the lead time of R. Then this may be because M did not supply it properly. So we need to look at M's stock shortage.

<Figure 4-7> M Out-of-Stock Change



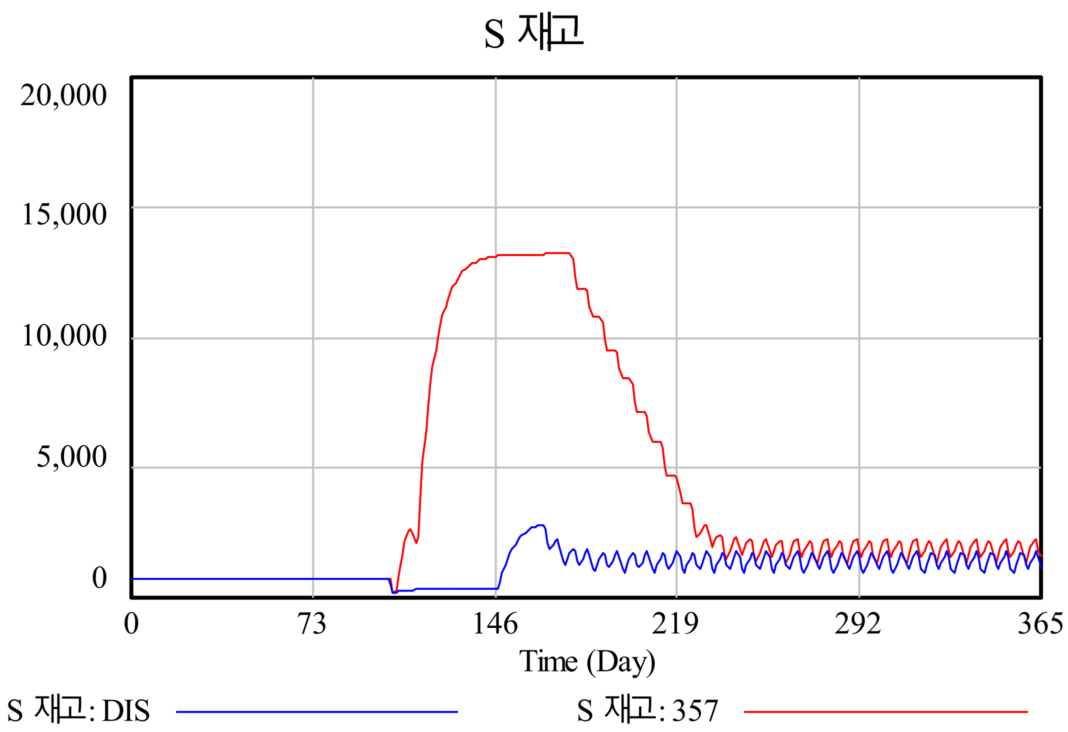
The DIS inventory shortage for the period is greater than the 357 stock shortfall. This is due to M's failure to keep up with changes in demand and target supply lines. When there is a big change in the quantity demanded, it is accepted quickly, but it is because the level of the desired inventory (supply line) has risen late. This is the result of delays.

<Figure 4-8> M inventory comparison according to information sharing



If information is shared, it can be seen that the whip effect is greatly reduced. The average and maximum values of the DIS are 1,039, 4,210, and 357 are 2,130, 11,533. The average was reduced by more than half, and the maximum was reduced by a larger margin. Sharing demand information reduces M inventory. However, the phenomenon that the blue line also recovers later than the red line was also seen in M stocks. Sharing demand information on resilience is expected to have a negative impact.

<Figure 4-9> S inventory comparison according to information sharing

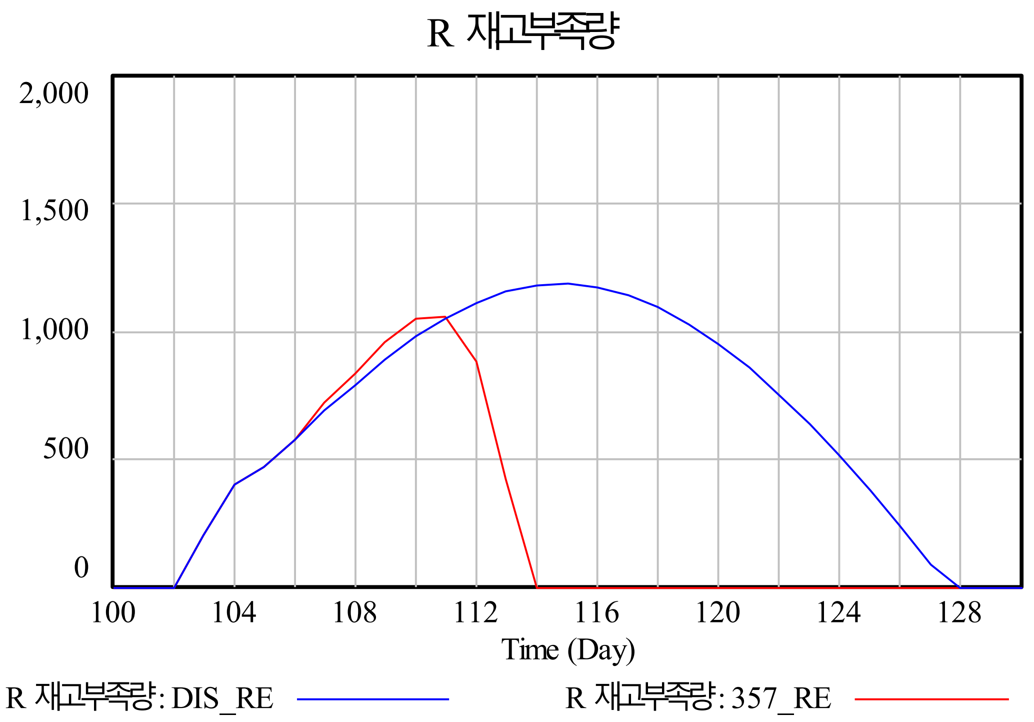


Looking at the effect of information sharing, the average and maximum values of S inventory DIS are 1,125 and 2,823. However, the average and maximum values of 357 are 4,068 and 13,209. The amount of inventory is also greatly reduced, and the whip effect is particularly large. As with M, there is a lag in the resilience of S.

M and S can significantly reduce inventory through information sharing, but the response to R and the end consumer may be jeopardized because of the lower inventory. Looking at the R shortage between 100 and 160 days, the DIS was 21.55, higher than the 18.58 in 357. It can be seen as a side effect of information sharing.

The R demand was partially adjusted to 100 + STEP (200, 101). This is the case when the demand from 100 increased to 300 from 101. At this time, the R inventory shortage is shown in the following <Figure 4-10>.

<Figure 4-10> Simulation of R outstocks



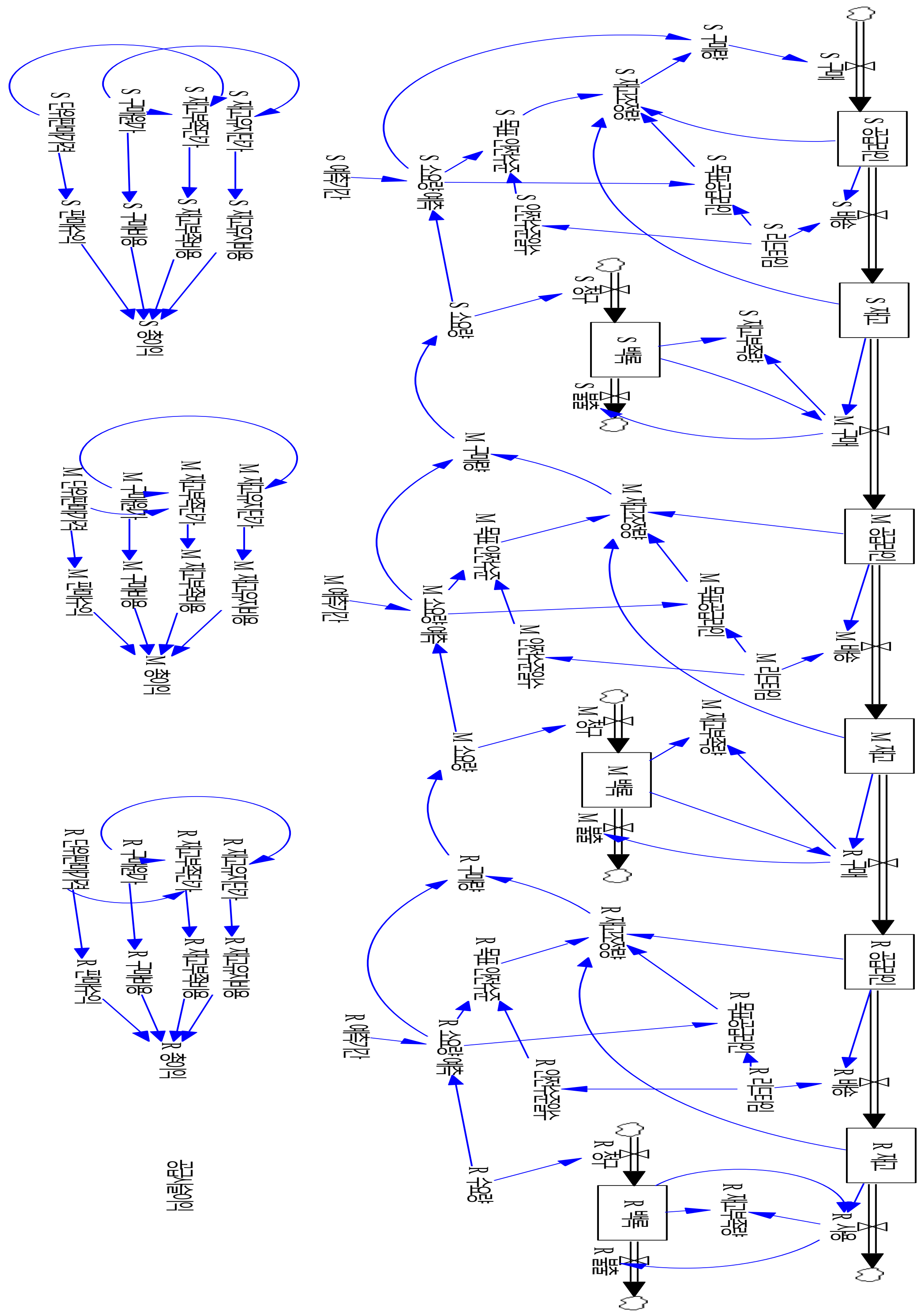
For 357, the stock shortage went from 114 days to zero. However, in the case of DIS, there is a shortage of inventory up to 128 days.

Sometimes there are supply chains where inventory shortages are fatal. A single inventory shortage can lead to a supply chain disruption.

2) Measuring benefits from sharing demand information

Inventory or shortages are important when designing supply chains, but cost and profit are more fundamental considerations. Unit purchase cost, inventory maintenance cost , inventory shortage cost, unit selling price, etc. are parameters that directly affect profit. We need to set these parameters in supply chain design to see what the structure of benefits is. Furthermore, it is necessary to look at the effect of sharing demand information in terms of profits.

<Figure 4-11>　Basic three-step supply chain model including cost-benefit　parameters



Various parameters were included at the bottom of　<Figure 4-11>.　The relation of the parameters is set as follows.

Supply chain profit=S gross profit+M gross profit+R gross profit

R gross profit = R sales revenue-R purchase cost-R Inventory shortage cost-R inventory maintenance cost

R Inventory Maintenance Cost = R Inventory*R Inventory Maintenance Unit Price

R Inventory Cost=R Stockout Unit Price*R Inventory Shortage

R purchase cost = R purchase * R purchase cost

R sales revenue = R unit selling price*R usage

R Inventory maintenance unit price = R purchase cost*0.01

R Insufficient unit price = (R unit selling price-R purchase cost)*0.01

R purchase cost = M unit selling price

R unit selling price=80

M gross profit = M sales revenue - M purchase cost - M Inventory shortage cost - M inventory maintenance cost

M Inventory Maintenance Cost = M Inventory * M Inventory Maintenance Unit Price

M Inventory Cost=M Inventory Shortage Unit Price*M Inventory Shortage

M purchase cost = M purchase * M purchase cost

M sales revenue = M unit selling price*R purchase

M Inventory Maintenance Unit Price=M Purchase Cost*0.01

M Insufficient unit price = (M unit selling price-M purchase cost)*0.01

M purchase cost=S unit selling priceM unit selling price
=40

S Gross profit = S sales revenue-S purchase cost-S Inventory shortage cost-S Inventory maintenance cost

S Inventory maintenance cost = S inventory * S Inventory maintenance unit price

S Inventory Shortage Cost = S Inventory Shortage Unit Price*S Inventory Shortage

S purchase cost = S purchase * S purchase cost

S sales revenue = M purchase * S unit selling price

S Inventory maintenance unit price = S purchase cost*0.01

S Inventory shortage unit price = (S unit selling price-S purchase cost)*0.01

S purchase cost=10

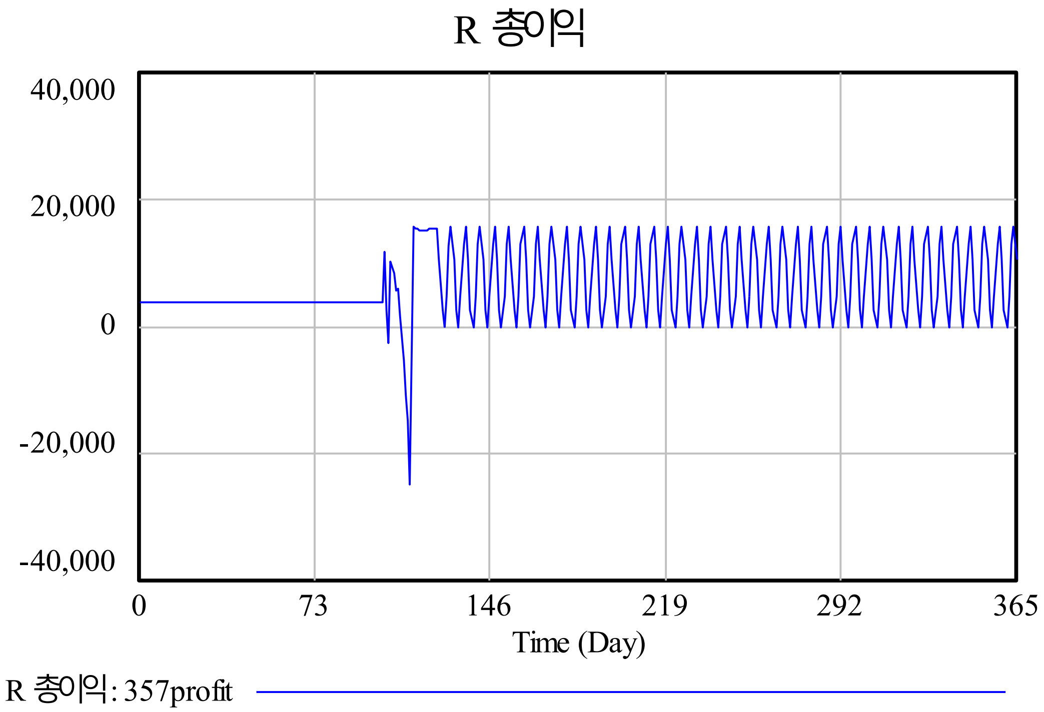
S unit selling price = 20

For the model 357 having lead times of R, M, and S 3 days, 5 days, and 7 days, respectively, it is based on following a method of predicting and purchasing the required amount for each. S is bought for $10 (in dollars for convenience) and sold to M for $20. M buys for $20 and sells for $40. R is bought for $40 and sold to an end customer for $80. It was assumed that each inventory maintenance cost would require 1/100 of the cost of each purchase. In general, it was assumed that the size of the warehouse would decrease as you move downstream in the supply chain, and the storage cost per unit of inventory would increase because it would be linked to perception. We included the cost of inventory shortages, which many companies generally do not consider. However, this must be taken into account for customer satisfaction. About 1% of the margin was applied as the unit price of insufficient inventory. The unit price of shortage of stock is also different in S, M, and R. Profitability reflected differences.

The R demand was 100 each, and from 101 to 200 demands, it was applied. For each inventory, refer to the graph in the previous chapter.

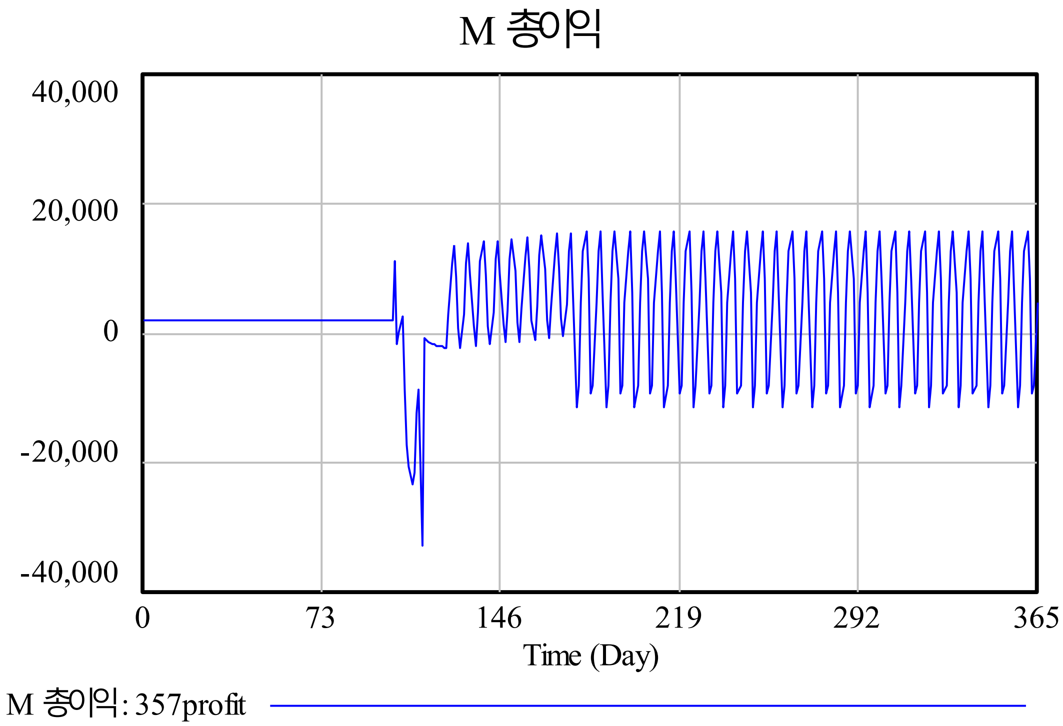
Looking at the gross profit of R, it appears as shown in the following figure.

<Figure 4-12> Change in R Gross Profit in Model 357



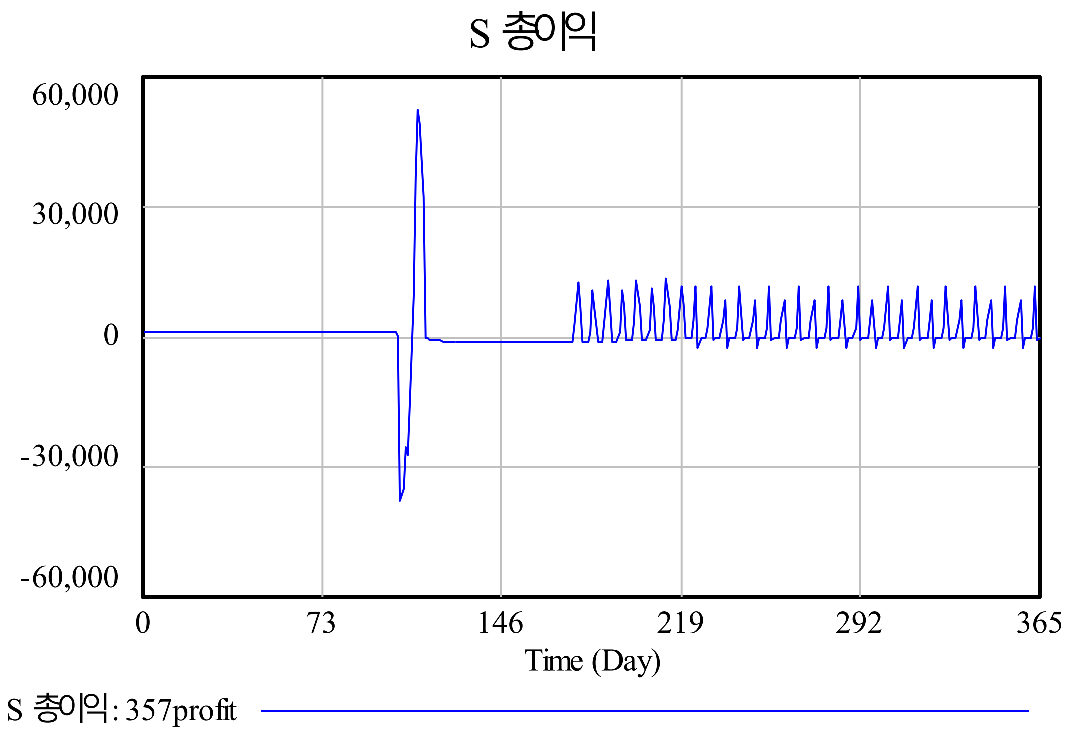
R gross profit fluctuates sharply after 101 days. This is because the inventory was exhausted due to the sudden increase in demand, resulting in a large amount of inventory shortage costs. R gross profit averages $6,624, with the biggest loss day reaching $24,990.

<Figure 4-13> Change in M Gross Profit in Model 357



M's average daily profit is $2,939, which is smaller than R. The maximum profit is $15,696 and the maximum loss is $32,748.

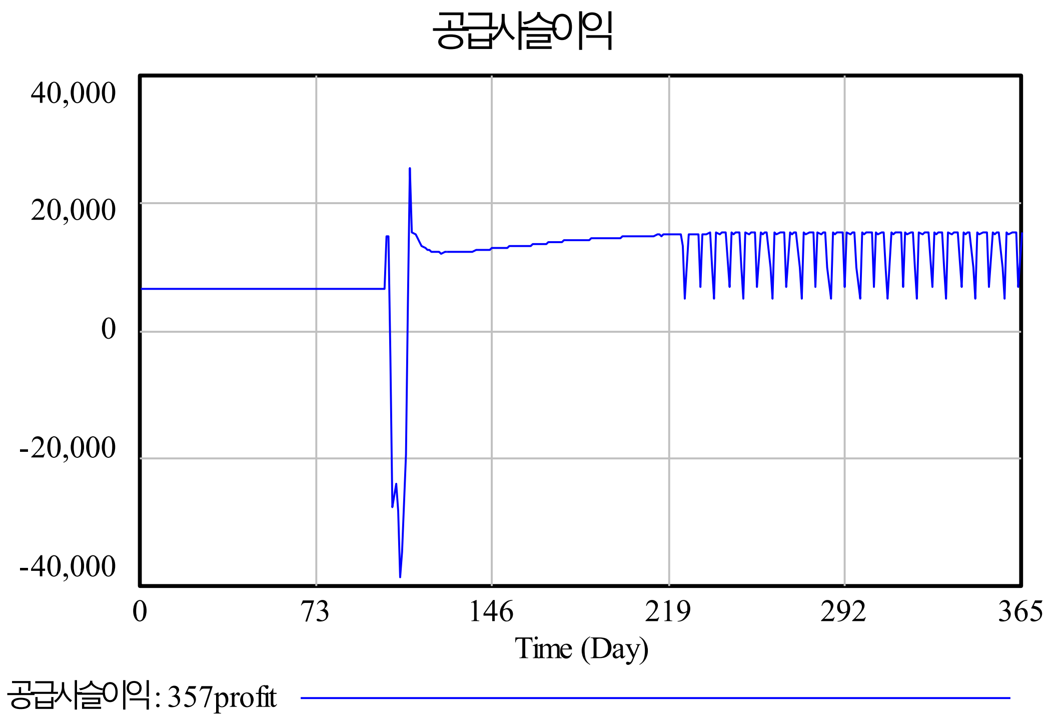
<Figure 4-14> Change in S Gross Profit in Model 357



S profit averages $1,307 per day. However, the maximum one-day loss is $37,858 and the maximum profit is $52,551. deviations take very large forms.

The resulting supply chain benefits are shown in the following figure.

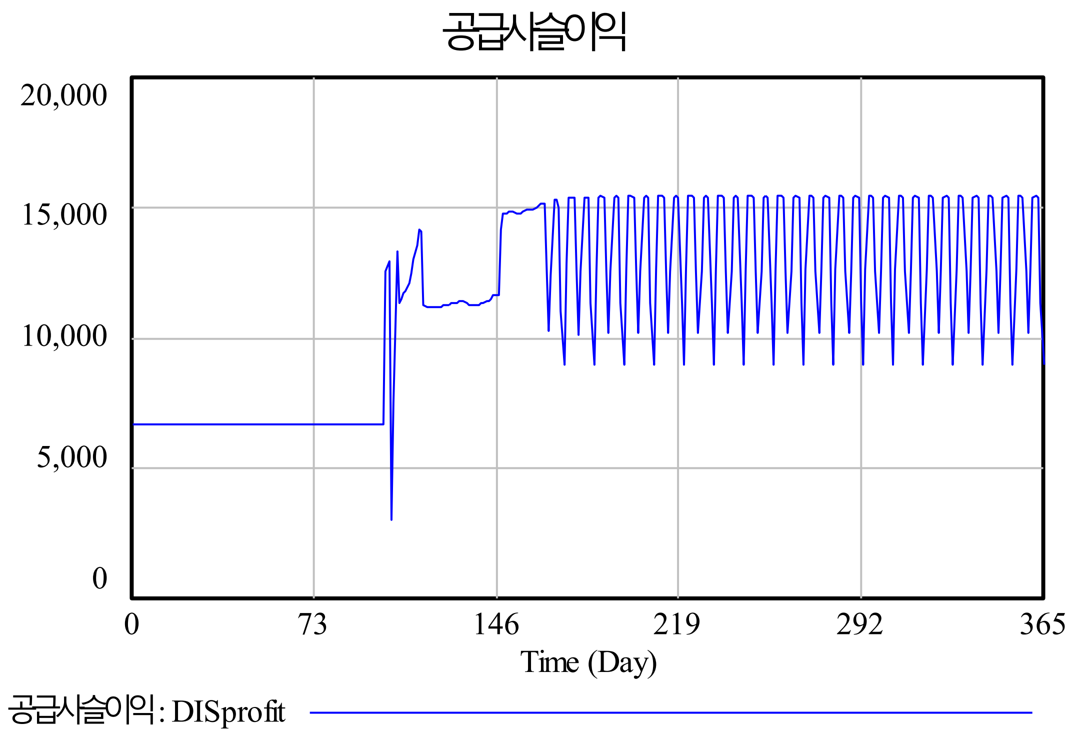
<Figure 4-15> Supply Chain Profit Change in Model 357



The average supply chain profit is $10,872 per day, with a maximum value of $25,439 and a maximum loss of $38,629.

In order to look at the increase or decrease of profit when demand information was shared, a bensim data file called DISprofit was created and simulation was performed by creating a bensim data file called DISprofit by changing the required quantity prediction relationship between M and S.

<Figure 4-16> Supply Chain Profit Change in the DIS Model



Roughly speaking, the model that shared demand information (DISpofit) is unique in that it has never become negative. This is the result of parameter setting, so it does not mean much, but the fact that the vibration width is small shows that the information idle effect is obvious.

<Table 4-1> Changes in Benefits of Information Sharing

	S Gross profit	M Gross Profit	R Gross profit	Supply Chain Benefits
DISprofit	1,593	3,126	6,620	11,340
357profit	1,307	2,939	6,624	10,842

It is worth recalling that the change in the volume of demand was not significant. It remained at 100 and then increased by 100 only once in 1 01, and was 200 from 102 to the end. There was only one change in demand. At this time, in the case of the DIS model, which accepts demand information quickly, there was an increase in supply chain profits of about 4.6%. Most of the benefits of this supply chain were accounted for by S gross profit. S's gross profit growth is 22%. M's gross profit growth rate is about 6%. R's gross profit growth rate is 0%.

Sharing demand information improves the interests of participants upstream in the supply chain. On the other hand, it can be seen that retailers who are in contact with demand do not have significant benefits from sharing information. It can be said that the motivation to actively share demand information disappears.

If R provides demand information, M and S increase profits. The profit of R does not increase. M and S must then give R a portion of their profits in exchange for demand information. S and M, even if they lose a small margin of their margins, should take steps to improve their overall profits.

The selling price of the S unit was lowered from \$20 to \$19, and the M unit selling price was also lowered from \$40 to \$38. Let's look at each other's interests and supply chain benefits.

Table < 4-2> Profit comparison when adjusting S unit selling price (→2019) and M unit selling price (→40 38)

	S Gross profit	M Gross Profit	R Gross profit	Supply Chain Benefits
S unit selling price = 19, Selling price in M units = 38	1,419	2,970	6,977	11,367
DISprofit	1,593	3,126	6,620	11,340
357profit	1,307	2,939	6,624	10,842

S lowered the unit price it sells to M from \$20 to \$19, resulting in a \$174 decrease in profit. However, this is an increase of \$112 compared to \$1,307 before the demand information was shared. M is \$1 lower from S but \$2 lower from R. So the M gross profit decreased by \$156 by lowering the price. But before the demand information was shared, it was only \$2,939. Instead, that's an increase of \$31.

R saw a decrease in profit due to sharing information, but S and M adjusted their prices, increasing their average daily profit to \$6,977. There may be differences in degree because the profit has increased by more than 5% by sharing demand information, but R is also worth sharing. For reference, supply chain profits increased when S and M adjusted prices.

In the supply chain, you cannot force participants to make unilateral sacrifices. Therefore, the parameters should be adjusted as long as mutual benefits increase. You can set the selling price in S units and the selling price in M units to maximize supply chain profits. This is when both parameters are at minimum values ($10). The reason is that the profit of S is offset by the cost of M, and the profit of M and the cost of R are offset. Ultimately, the sale of R (using R here) is when there is no shortage of inventory. When that happens, the losses of S and M become very large. It cannot be a win-win between supply chain participants.

Sharing information between supply chain participants can increase supply chain benefits. A trade-off between the costs and benefits of information sharing must be made. It seems to work like a zero-sum game, but it has some conundrum game features in the supply chain. Retailers at the end of the supply chain (R in this case) must make a sale to realize a profit. Therefore, if a retailer is unable to sell because of lack of inventory, it is difficult to expect an increase in profits.

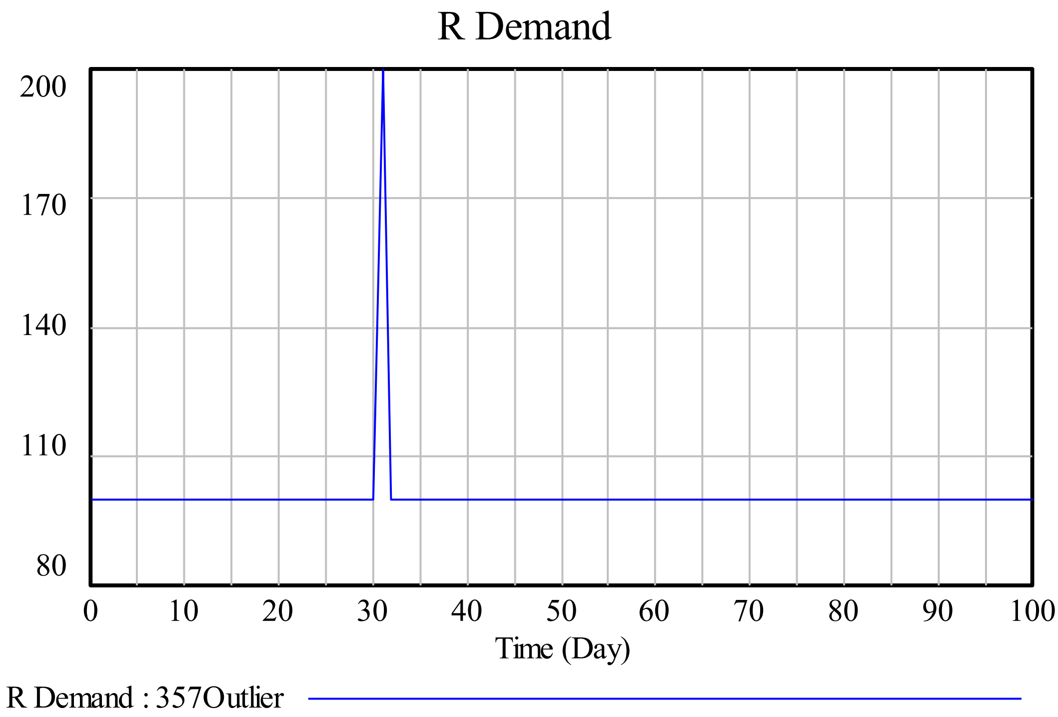
Profits are shared or allocated through various contracts or negotiations. At this time, it is necessary to simulate how much profit each participant should expect, and system dynamics is a good decision-making tool.

3) Necessity of e-store management

The basic data when managing the right amount of inventory is demand. When accepting demand, demand is sometimes distorted by mistakes, sometimes by unusual demand behavior. It is difficult to judge in the process of processing the actual data, but it is still often much more advantageous to process it with this store. Here, we look at how an anomaly affects the supply chain when it occurs in a single day.

Suppose demand occurs for 0 to 100 days, but on the 31st day, the demand is entered twice by mistake. See RMS model 357.

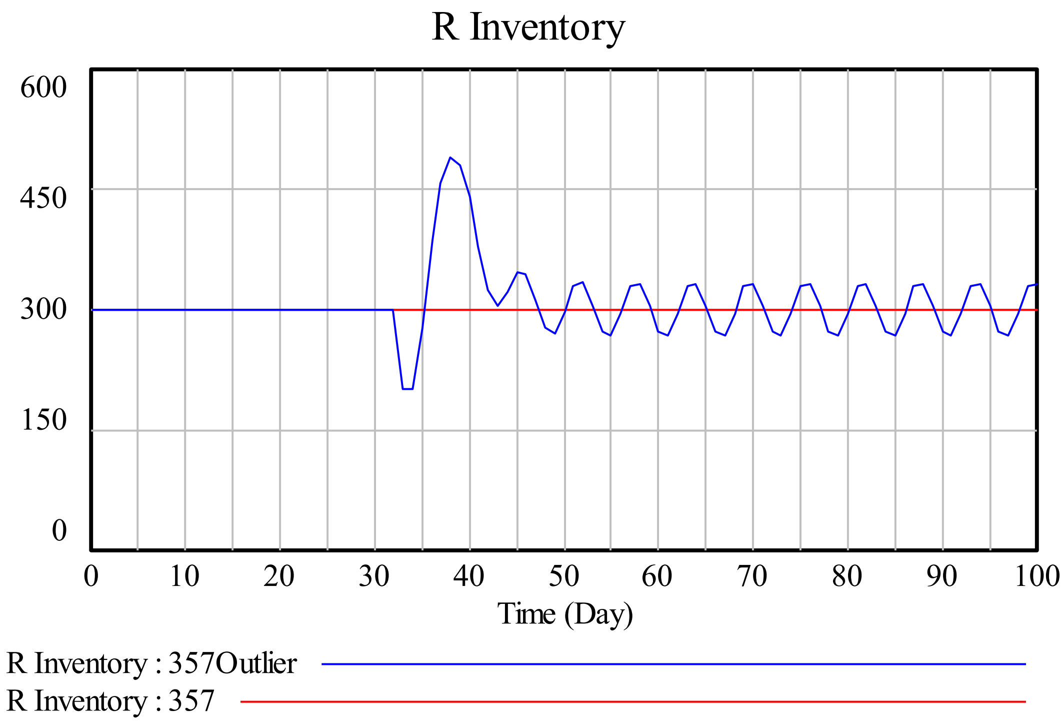
<Figure 4-17> When there is an anomaly in demand



When an outlier occurs in demand, when the demand is judged to be the real demand, or when the outlier is not removed, the following phenomenon may occur.

First , R Inventory appears as shown in the following figure.

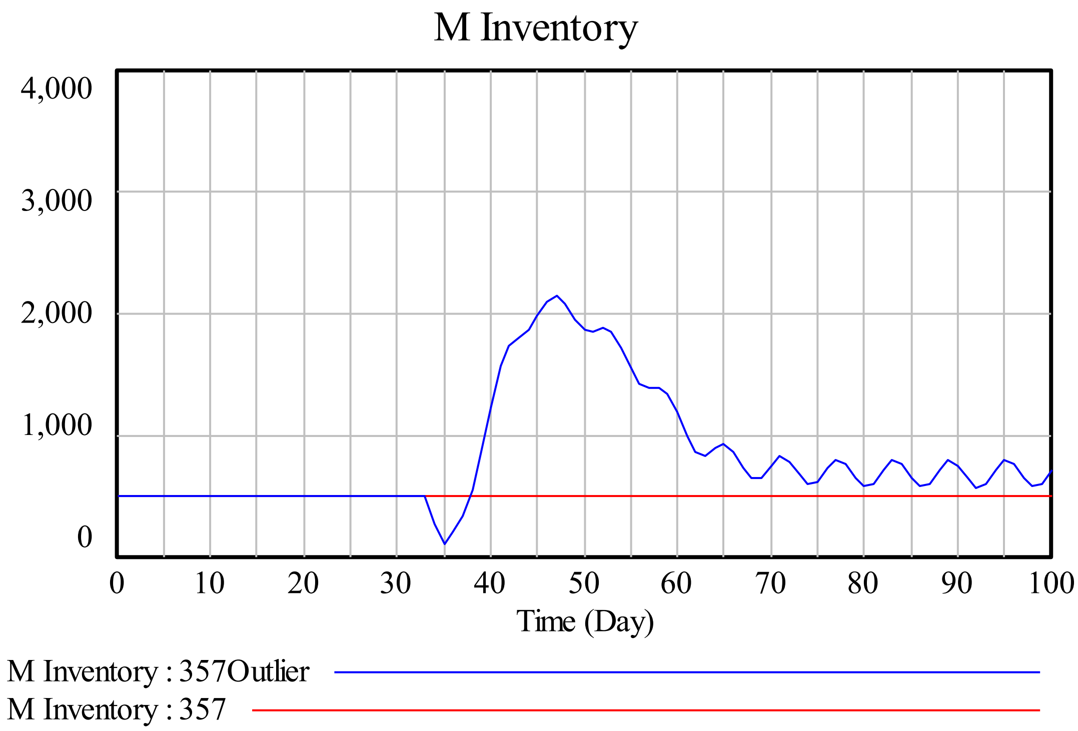
<Figure 4-18> Impact of Anomalies on R Inventory in a Single Day



In <Figure 4-18>, the red line is 357 (the base model is 100 continuously from 0 to 100), the blue line is 200 on the 31st and 100 on the rest of the day. Despite changing for only one day, R inventory continues to show waves from the 31st. Around 37 days, a relatively strong whip effect may occur. Since the wave shows within a certain range after 50 days, it can be considered balanced, but even if the period is extended, it will not become a single straight line and the wave will continue. The average inventory over 101 days is 307.72 with a standard deviation of 42.28 for 357 o utlier, compared to 300 for 357o utlier.

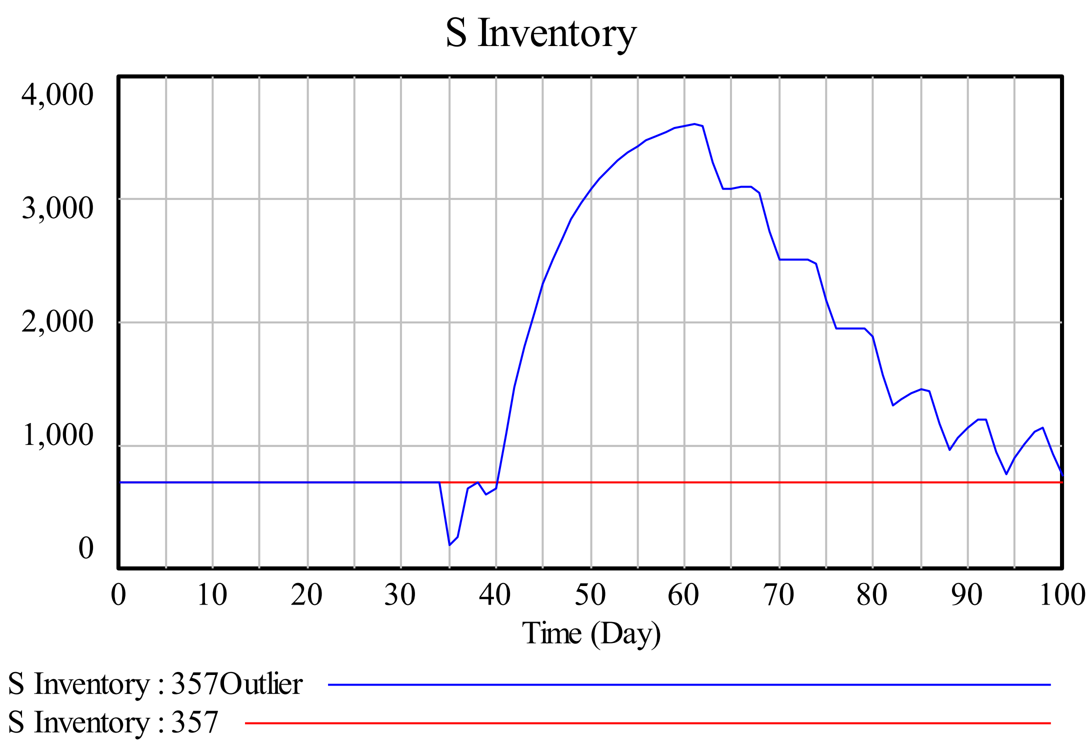
M inventory faces greater changes than R inventory.

<Figure 4-19> Impact on M inventory if an outlier occurs in a single day



357Outlier's M stock is up to over 2,000. Assuming that M's target stock days are 5 days, if there are no outliers, keep 500 as they are. However, there has only been a change in demand for one day, and M's inventory has a severe whiplash effect. The reason why it does not converge to 5 00 even after 100 days is that the order volume of R keeps changing. This is due to the fact that R stocks continued to fluctuate. The M stock mean of the 357 model is 500 and the standard deviation is 0. On the other hand, the mean of 357Outliers is 832.52 and the standard deviation is 489.32. It's a tremendous effect.

<Figure 4-20> Impact on S inventory if an outlier occurs in a single day



S There is also a significant difference in inventory. Since R and M have already shown the whip effect, the whip effect is bound to be greater for S who accepts it. Demand for R has only been above a one-day mark, with an increase of 100 units, with S inventory rising to a high of 3,617 units. 3 The mean of 57 Outliers is 1,590, and the standard deviation is 1,050. Of course, the S stock mean of 357 is 700 and the standard deviation is 0.

In information sharing, e-shop management is essential. The foregoing occurred in the absence of peacetime demand uncertainty, so the effect was maximized. If there is day-to-day demand uncertainty, it will have a smaller effect. Defining and removing foreign stores when they are not well distinguishable means that they are difficult to track when everyday uncertainty exists.

A method of including a module to remove outliers through Kelman filtering, or to control the effect of this store by continuously generating noise (noise) can be used. The explanation of this part is considerably more difficult than the content of this book, so it is omitted here.

Chapter 5

The impact of heuristics on the supply chain

Heuristics on the Supply Chain

Looking at a series of numbers, people have a biased perception. Some use only part of the numbers, or they are sure that a different pattern will emerge. Both the limits of knowledge and the limits of information operate. In this sense, bounded rationality, as Simon (1965) talked about, is a characteristic that people have universally.

Supply chain management also requires recognizing various numbers. So far, the numbers you've mainly covered are demand and lead time. For these numbers, people also trigger heuristics. Heuristics are a kind of heuristic technique, rules adopted by one's own know-how or cognitive limitations. In general, heuristics contain bias.

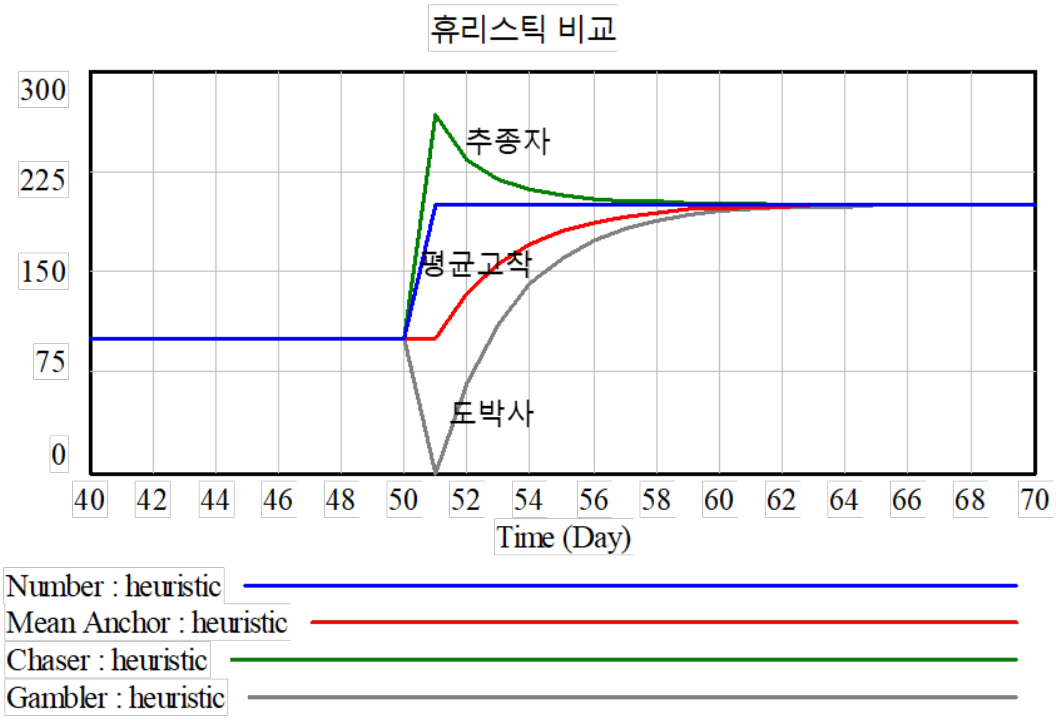
There are various heuristics, and here we will look at three heuristics. The first is Mean Anchor Heuristic. It is a heuristic that sticks to the mean and moves to a very slowly changed value. Although it varies considerably depending on the race and related experiences, it is the heuristic that most people have. In comparison, there are heuristics that are very sensitive to change. It's called chase heuristic. If it changes from 100 to 200, expect 300 next. I think any change will happen the same next time.

In contrast, the gambler heuristic expects it to return to the average. If 100 comes out consecutively and 200 comes out one day, it is believed that 0 must occur the next day to return to the mean.

How long will you predict? There are different patterns depending on how long the adjustment will be made, but here we want to understand the extent of the impact on the supply chain based only on its authenticity.

<Figure 5-1> shows how three heuristics appear when a number changes from 100 to 200.

<Figure 5-1> Examples of 3 Heuristics



When a number (blue line) changes, the mean adherent slowly follows, the follower changes larger and then softens, and the Taoist moves in the opposite direction and gradually converges. In Vensim, heuristics must be entered as relations. Using Vensim's own function, or finding a simple way to express it, we defined the relations of the three heuristics as follows.

Mean sticking prediction = SMOOTH (number, smoothing period)

FOLLOWER =FORECAST(number, adjustment time, 1)

Gambler = 2*Perceived Average-Number

If a participant in the supply chain has these characteristics, it affects the entire supply chain. Sometimes it can counteract the whiplash effect, sometimes it can amplify it. Let's take a look at the characteristics of having three heuristics for the numbers demand and lead time.

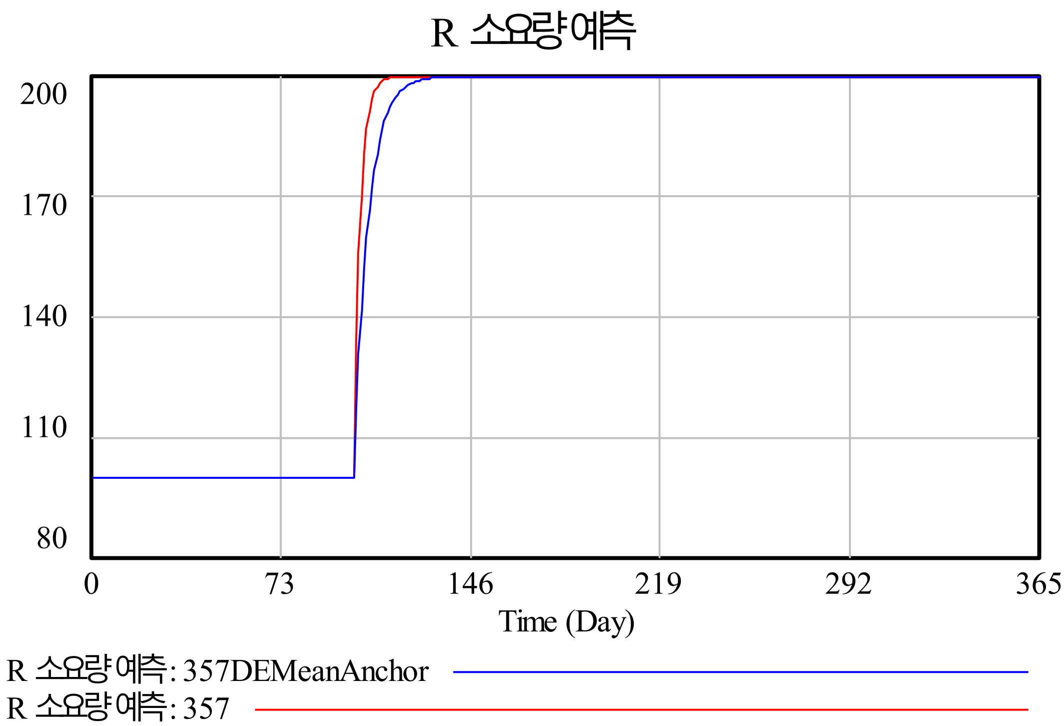
1) Heuristics in demand information processing

The lead time was fixed at 3, 5, and 7, and it was assumed that the demand changed only once to 100 + STEP (100, 101). Simulations were performed for 366 days from 0 to 365. It was assumed that all supply chain participants had the same heuristic.

(1) Effects of mean sticking heuristics

The demand is the same, but the forecast of the required amount of R that reflects it varies.

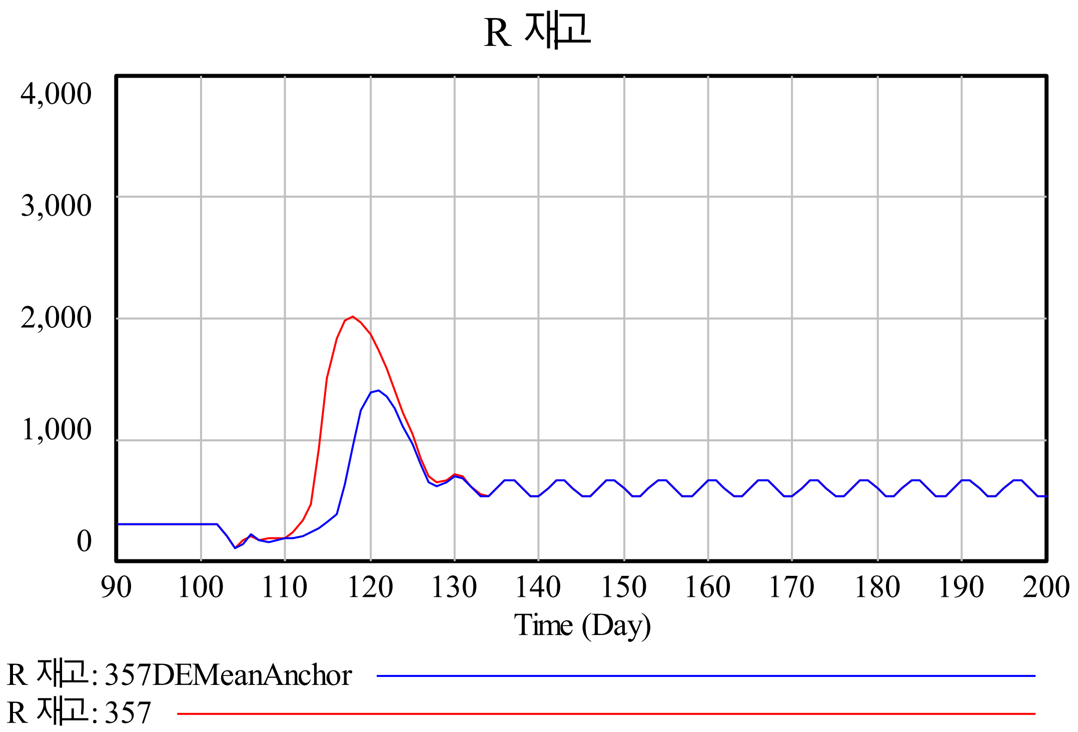
<Figure 5-2> Comparison of R requirement prediction of base model 357 and mean sticking heuristics



It is stuck in the average for longer and changes slowly. <Convergence to 200 late in Figure 5-2> is the mean sticking heuristic. Here, the prediction period in the SMOOTH function is assumed to be twice as high as the normal (lead time). Both M and S have mean sticking heuristics.

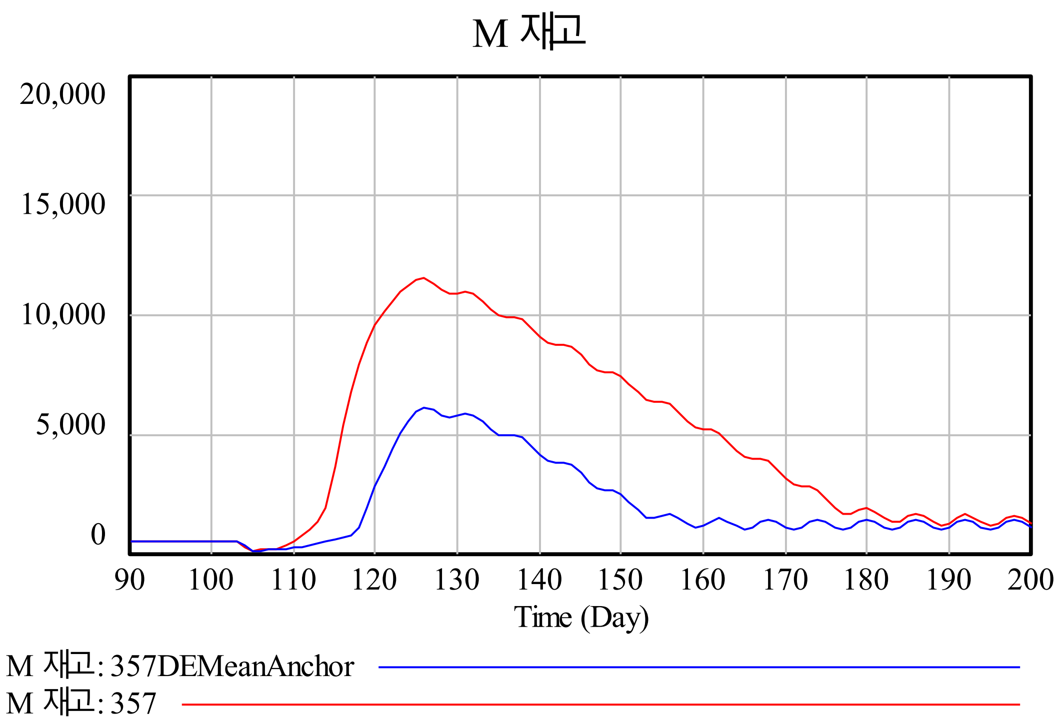
The R inventory accordingly is shown in the following <Figure 5-3>.

<Figure 5-3> R inventory comparison of basic model (357) and average sticking heuristics



When the average sticking heuristic is activated, it can be seen that the overshoot becomes smaller. It only changed once, because it moved slowly.

<Figure 5-4> R inventory comparison of basic model (357) and average sticking heuristics



M inventory also saw a decrease in overshoots. S inventory has also seen a significant reduction in overshoots.

Table 5-1> < Inventory Comparison of Basic Model 357 and Mean Sticking Heuristic Model

model	S Stock	M Stock	R Stock	Supply Chain Benefits
357	4,068	2,130	538.84	10,872
Demand average sticking	1,654	1,282	515.62	11,295

In the case of mean sticking heuristics, it seems to have a positive effect on the supply chain. However, it is worth knowing that this is only positive for specific demand. If demand shows a long-term trend, the average sticking will suffer. Therefore, the average sticking heuristic should not be perceived as a good thing. However, it is significant to show that a single heuristic, called a heuristic, can significantly affect inventory volumes and profits in the supply chain.

3 The variables and formulas that changed in the transition from the57 model (the model with

supply chain benefits in <Figure 4-1>) to the model of mean sticking heuristics to demand are as follows:

R prediction period = 6

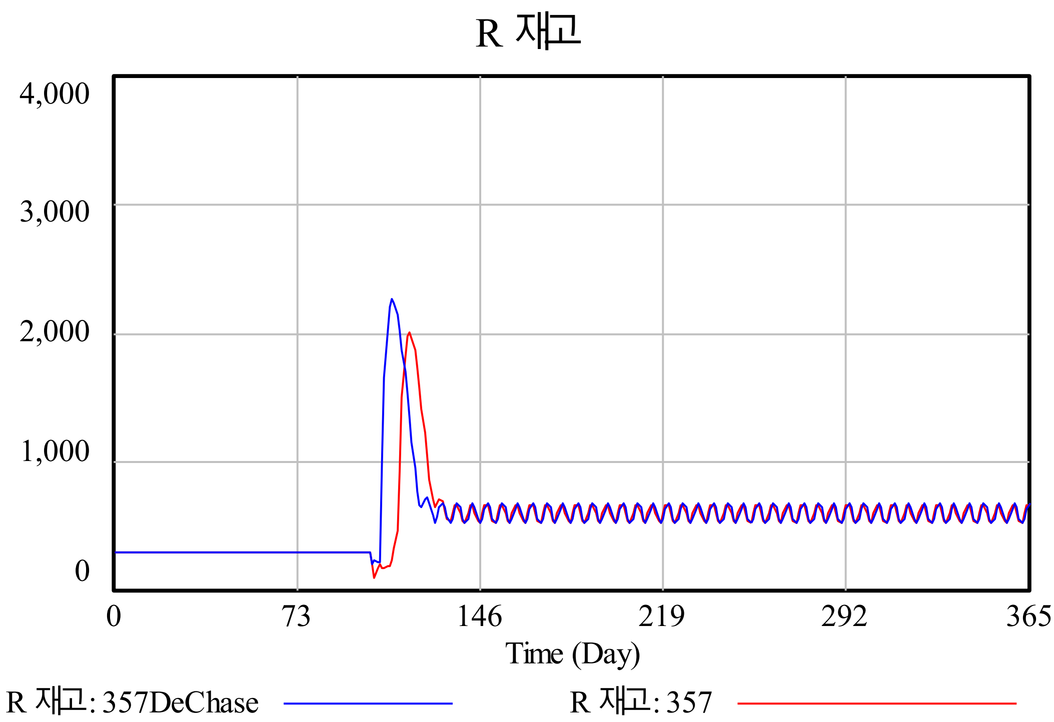
M Forecast period = 10

S Prediction period = 14

(2) Supply chain impact of demand-following heuristics

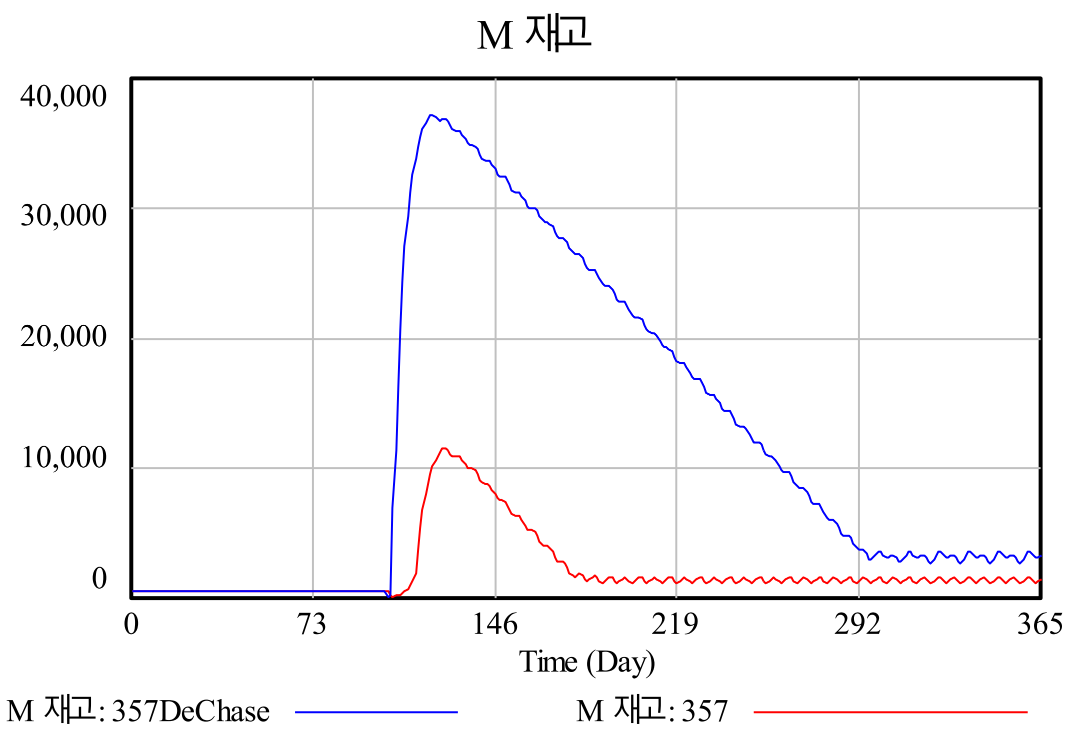
With the demand-following heuristic, the R inventory is larger than the 357 model, as shown in < Figure 5-5>, but it quickly finds balance.

<Figure 5-5> R inventory comparison between the base model (357) and the demand-following heuristic model



The M inventory accordingly is shown in the following <Figures 5-6>.

<Figure 5-6> M inventory comparison between the base model 357 and the demand-following heuristic model



In the case of demand-following heuristics, it can be seen that it greatly evokes the whip effect compared to the basic model. M inventory has not reached equilibrium for about 200 days.

S inventory is even more stark. Due to the demand-following heuristic, S inventory shows an incomparably higher inventory volume than the 357 model. The S inventory of 357 is not even shown in the graph. It didn't show up because it made such a big difference. That means it looks almost zero.

<Figure 5-7> S inventory comparison between the basic model (357) and the demand-following heuristic model

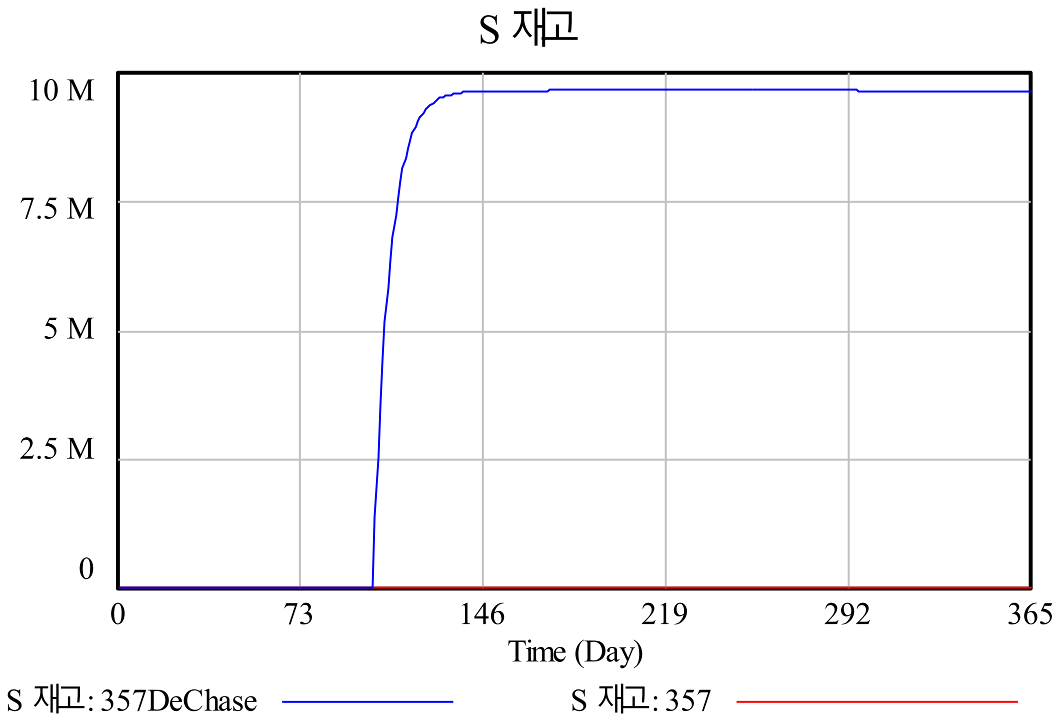


Table 5-2> illustrates that the use of demand-following heuristics can lead <to supply chain management failures. The demand-following heuristic only changed one relation, and the ripple effect on the supply chain was analyzed to be very large.

<Table 5-2> Inventory Comparison of Basic Model 357 and Demand-Following Heuristic Model

model	S Stock	M Stock	R Stock	Supply Chain Benefits
357	4,068	2,130	538.84	10,872
Demand following	6.778M	11,831	555.97	-931,881

3 The variables and formulas changed in the transition from the57 model (the model containing supply chain profits in <Figure 4-1>) to the model of demand-following heuristics are as follows:

R Demand Forecast = FORECAST(R Demand, R Forecast Period, 1)

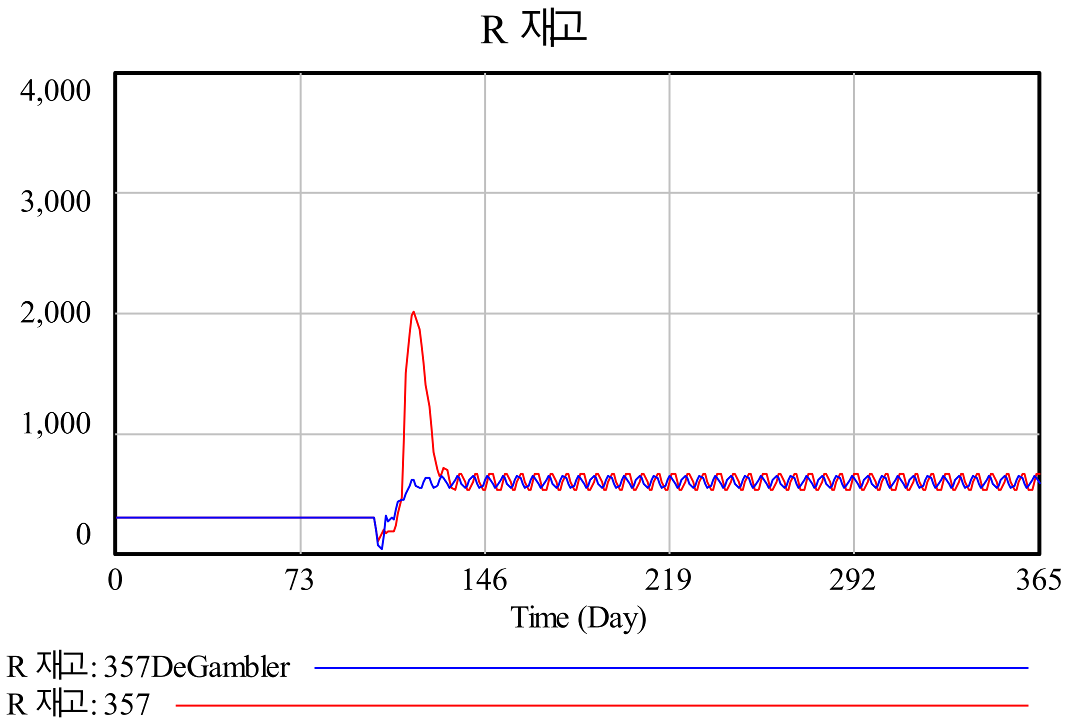
M Requirement Forecast = FORECAST(M Requirement, M Forecast Period, 1)

S Requirement Forecast = FORECAST(S Requirement, S Forecast Period, 1)

(3) The impact of gambler heuristics on the supply chain

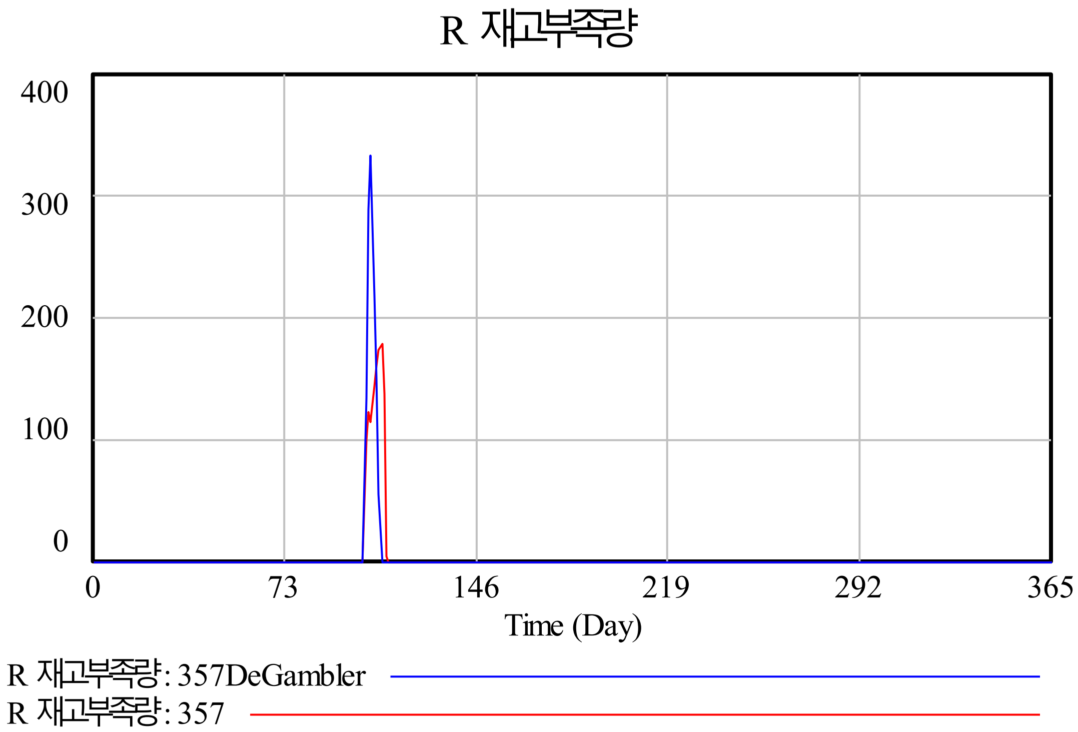
When the gambler heuristic is applied to the supply chain, the R inventory appears as shown in the following <Figure 5-8>.

<Figure 5-8> R inventory comparison between the base model (357) and the gambler heuristic model



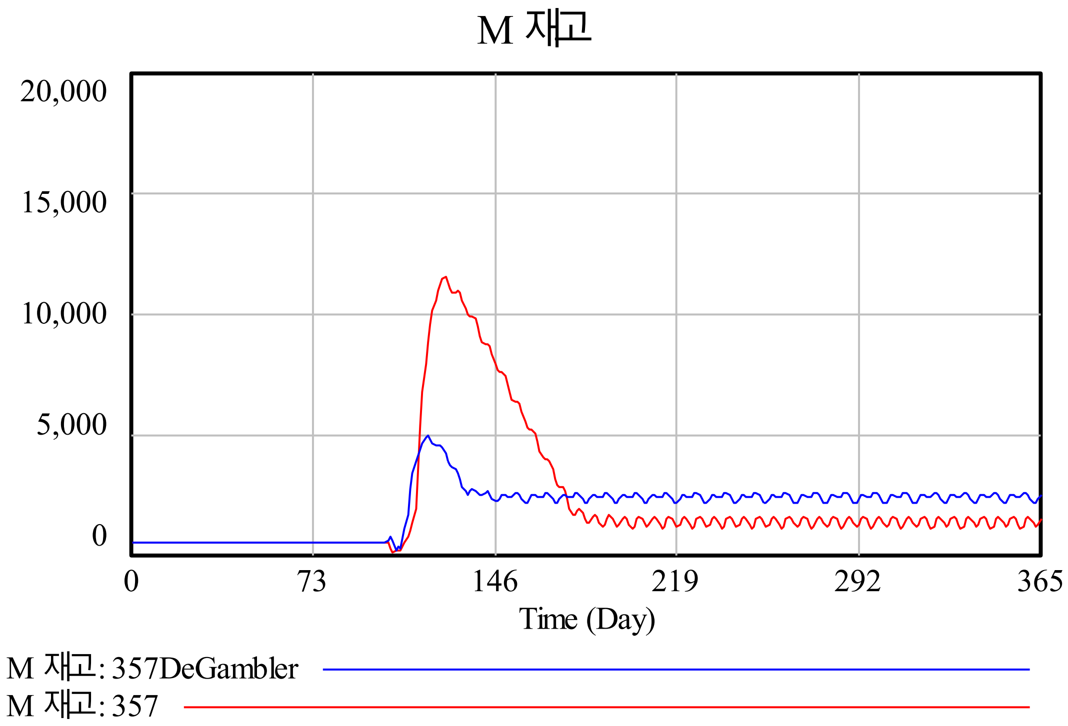
It appears that the overshoot of the model with the gambler heuristic is significantly reduced compared to the 357 model. The R inventory shortage of the gambler heuristic model is shown in the following <Figure 5-9>.

<Figure 5-9> R Out-of-Stock Comparison between the Base Model 357 and the Gambler Heuristic Model



The R stock shortage at the time of the overshoot is much higher for the model with the gambler heuristic than for the 357. It seems that they chose to slowly compensate for the risk of shortage of inventory over time rather than increasing it with order volume. Accordingly, the overshoot of M inventory is also low.

<Figure 5-10> M stock comparison between the base model (357) and the gambler heuristic model



<Table 5-2> Inventory Comparison of Basic Model 357 and Gambler Heuristic Model

model	S Stock	M Stock	R Stock	Supply Chain Benefits
357	4,068	2,130	538.84	10,872
Gambler	8,100	1,939	504.55	10,366

Applying the gambling company heuristic, it can be seen that R inventory and M inventory decreased slightly, but S inventory increased significantly. It is understood that R took the risk by incurring an inventory shortage, but this became a source of fire and affected S. This is because, despite the large negative numbers occurring in the prediction of the requirements of M and S, the desired value could not be purchased according to the rule that negative numbers cannot be ordered.

3 The variables and formulas that changed in the transition from the57 model (the model containing supply chain profits in <Figure 4-1>) to the model of the gambler heuristic for demand are as follows:

R Perceived demand volume average = SMOOTH (R demand, R forecast period)

R Requirement Prediction=2*R Perceived Demand Average-R Demand

M Perceived Demand Mean = SMOOTH (M Demand, M Forecast Period)

M Demand Prediction=2*M Perceived Demand Average-M Demand

S Perceived demand volume average = SMOOTH (S quantity demanded, S forecast period)

S Quantity required prediction=2*S Perceived demand average-S Demand quantity

2) Heuristics in lead time processing

Not only demand, but also lead time is a number, and heuristics are triggered to recognize this.

(1) Mean sticking heuristic for littime

First, R requirement = 100 was changed, and each lead time was changed as follows. Since no demand change occurred, a comparison of profits with the 357 model is not necessary.

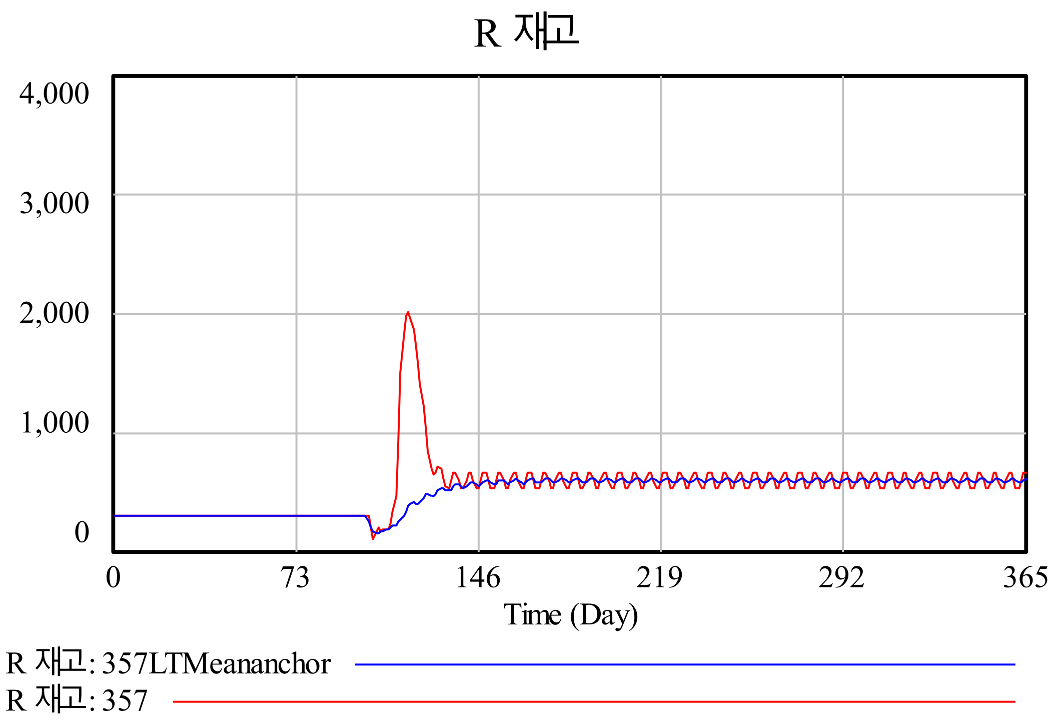
R Lead Time = 3+STEP(3, 101)

M Lead Time = 5+STEP(5, 101)

S lead time = 7+STEP(7, 101)

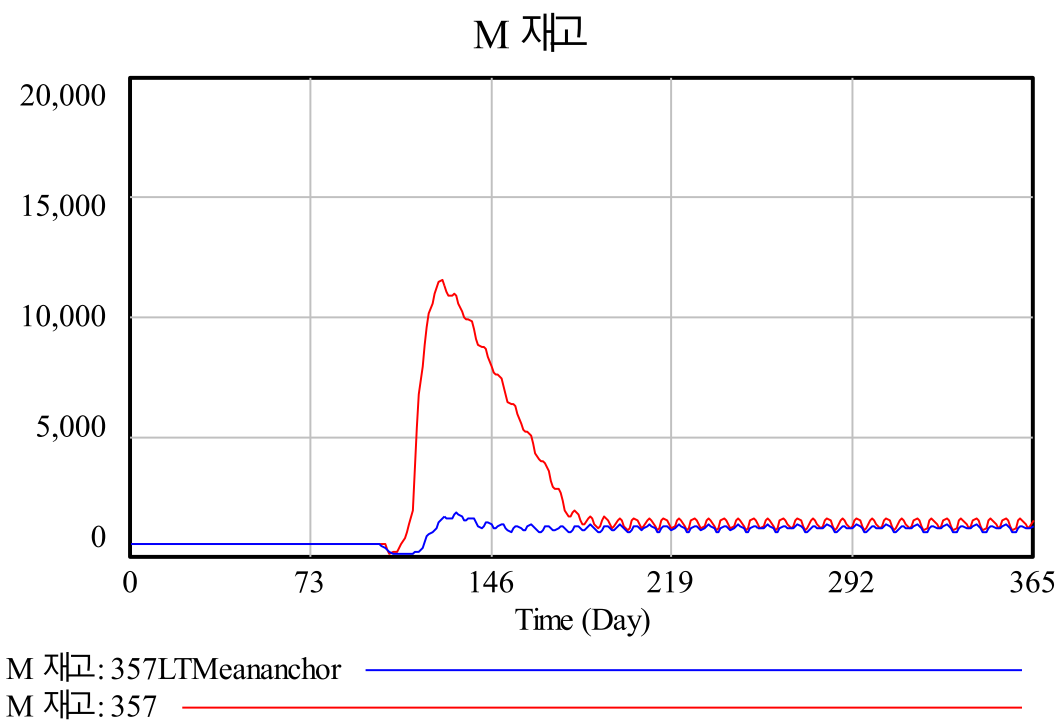
R inventory is shown in the following <Figure 5-11>.

<Figure 5-11> R Inventory Comparison of 357 Models and Lead Time Mean Stuck Heuristic Models



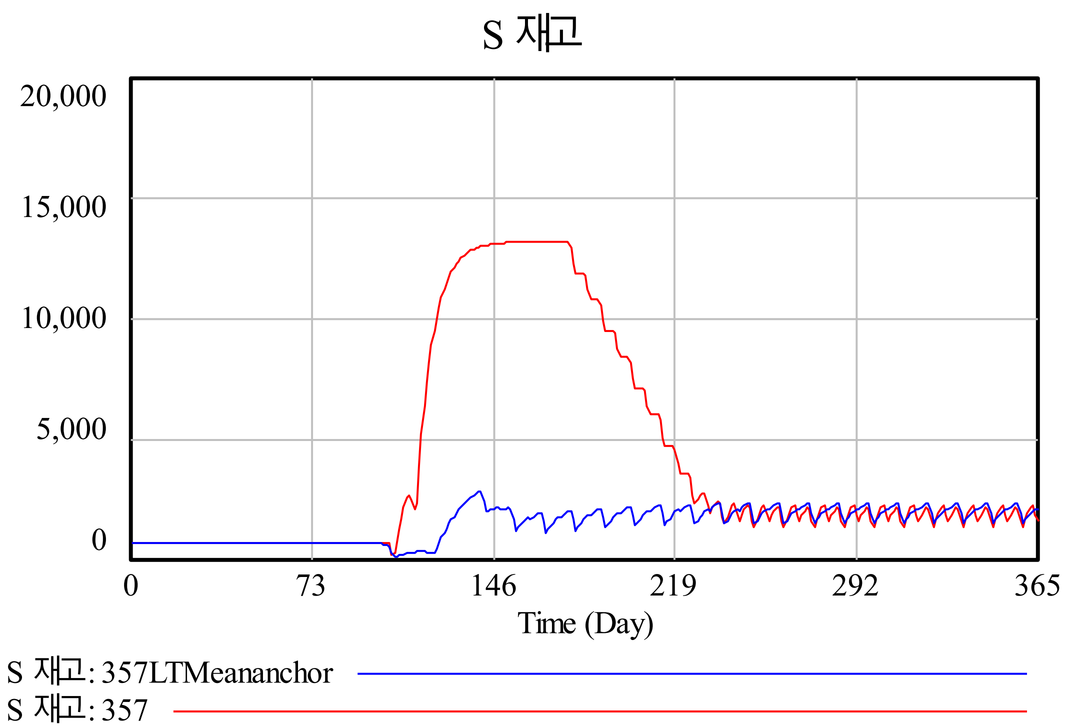
A characteristic of the lead time average sticking heuristic model is that no overshoot occurs. Nor did there be an R stock shortage. However, when it goes into equilibrium after about 150 days, it follows a structure almost similar to the 357 model. The 357 model showed the same pattern even though the demand was 200 and the 357LTMeananchor model was 100. This is because the lead time has been increased from 3 to 6 days.

<Figure 5-12> M Inventory Comparison of 357 Models and Lead Time Mean Stuck Heuristic Models



M inventory of lead time average sticking heuristic models also experienced very little overshoot due to a slight M shortage.

<Figure 5-12> M Inventory Comparison of 357 Models and Lead Time Mean Stuck Heuristic Models



Looking at the difference in S inventory, the 357 model has an average of 4,068 units per day, while the 357LTMeananchor model averages 1,504, which is less than half. Sudden increases in demand and sudden increases in lead times have the same consequences for target supply lines and target safety levels, but have different effects on inventories.

(2) Heuristics following for littime

To implement the lead time following heuristic, the following variables and relations were set. Lead time and quantity demanded are the same as the average sticking heuristic.

R Lead Time Forecast = FORECAST(R Lead Time, R Forecast Period, 1)

R Target Supply Line = R Requirement Forecast*R Lead Time Forecast

R Safety Level Days = R Lead Time Prediction

M Lead Time Forecast = FORECAST(M Lead Time, M Forecast Period, 1)

M Target Supply Line = M Requirement Forecast* M Lead Time Forecast

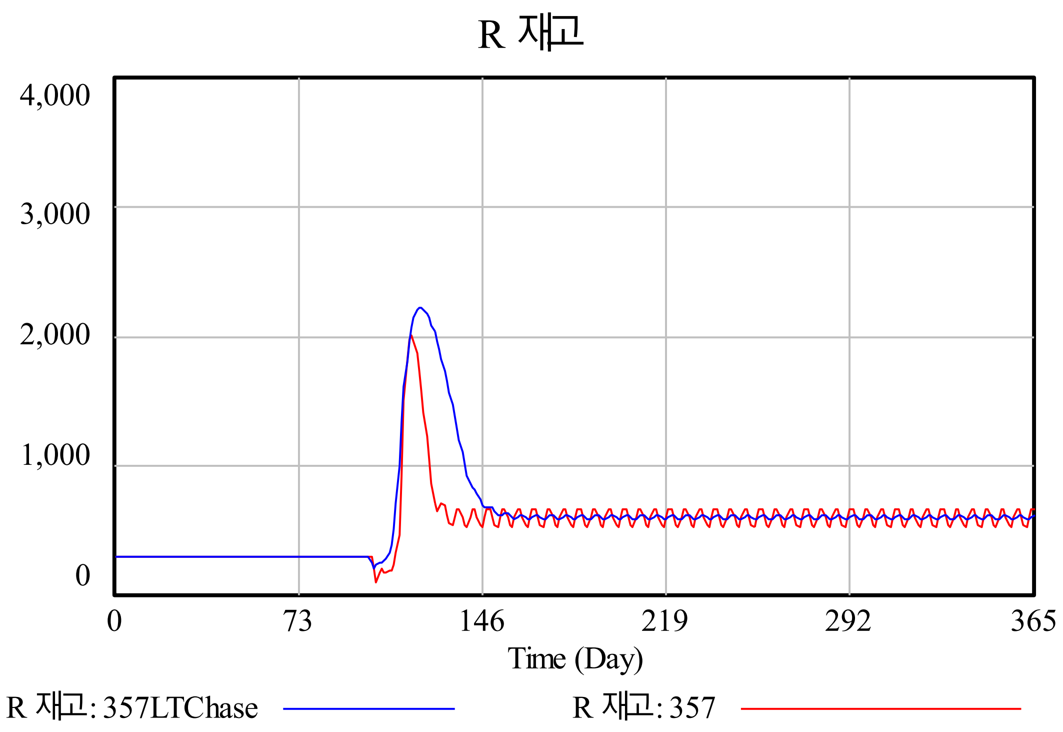
M Safety Level Days = M Lead Time Prediction

S Lead Time Forecast = FORECAST(S Lead Time, S Forecast Period, 1)

S Target Supply Line = S Prediction of Requirements* S Prediction of Lead Time

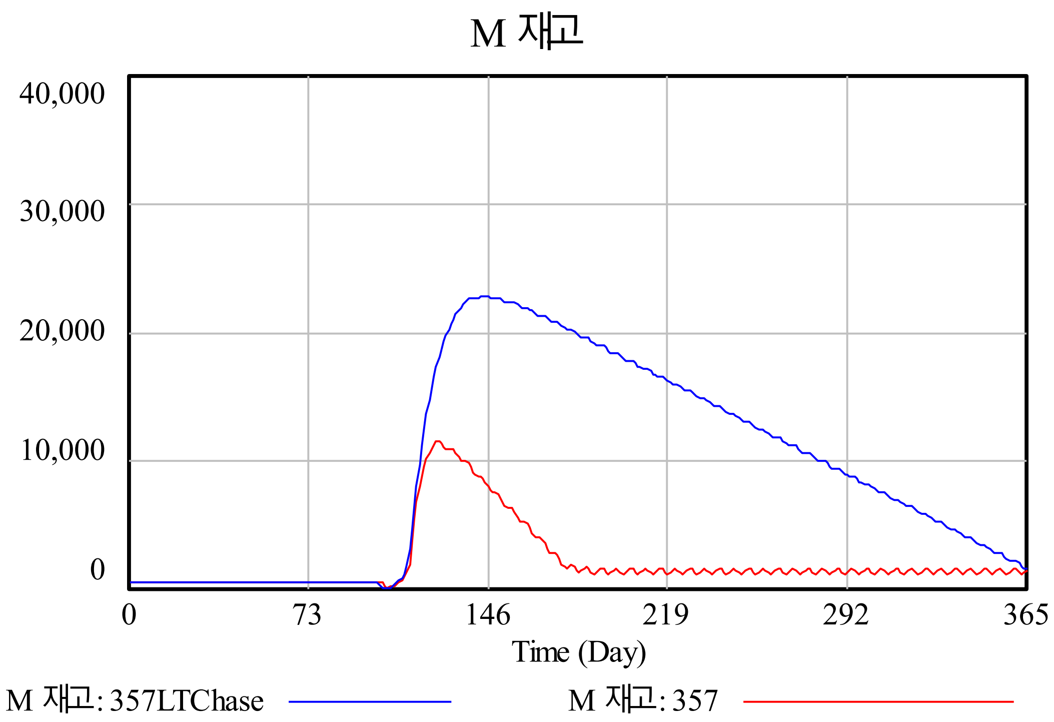
S Safety Level Days = S Lead Time Prediction

<Figure 5-14> R Inventory Comparison of 357 Models and Lead Time Tracking Heuristic Models



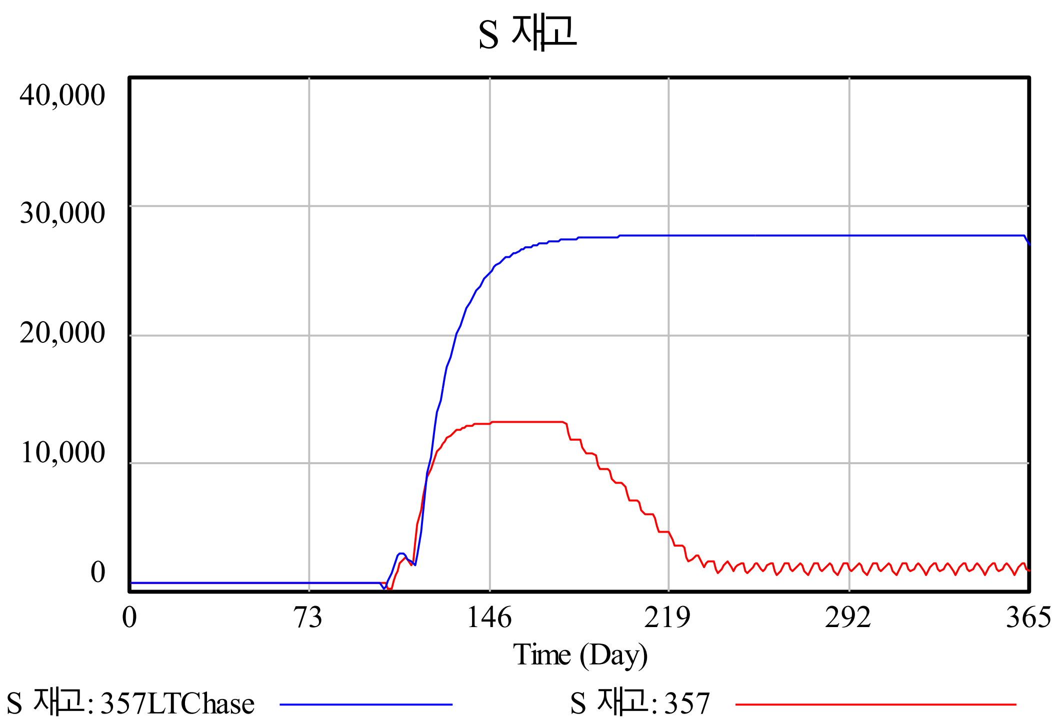
When the following heuristic for lead time is reflected, the overshoot of R stock is larger and lasts longer than the 357 model. From the one-day average of 538.84, it increased by more than 10% to 599.06. Even though the demand for the following heuristic is 100, it will have more inventory.

<Figure 5-15> M Inventory Comparison of 357 Models and Lead Time Tracking Heuristic Models



In M inventory, there is a much larger difference than in R inventory. Compared to 2,130 (357 models), it will have 9,250 units as a daily average. Once the overshoot occurred, it did not resolve after 365 days.

<Figure 5-16> S inventory comparison between 357 models and lead-time tracking heuristic models



If you have a lead-time following heuristic, you will also have a fairly large amount in S inventory because of the large overshoot. When it comes to lead time perceptions in the supply chain, it shows that the following heuristics are having a very bad effect.

(3) Gambler heuristics for lead time

The following variables and formulas were changed to reflect the gambler heuristic in lead time recognition.

R Perceived lead time mean = SMOOTH (R lead time, R predicted period)

R Lead Time Forecast = 2*R Perceived Lead TimeAverage-R Lead Time

R Target Supply Line = R Requirement Forecast*R Lead Time Forecast

R Safety Level Days = R Lead Time Prediction

M Perceived Lead Time Average = SMOOTH (M Lead Time, M Predicted Period)

M Lead Time Forecast = 2*M Perceived Lead Time Average-M Lead Time

M Target Supply Line = M Demand Forecast*M Lead Time Forecast

M Safety Level Days = M Lead Time Prediction

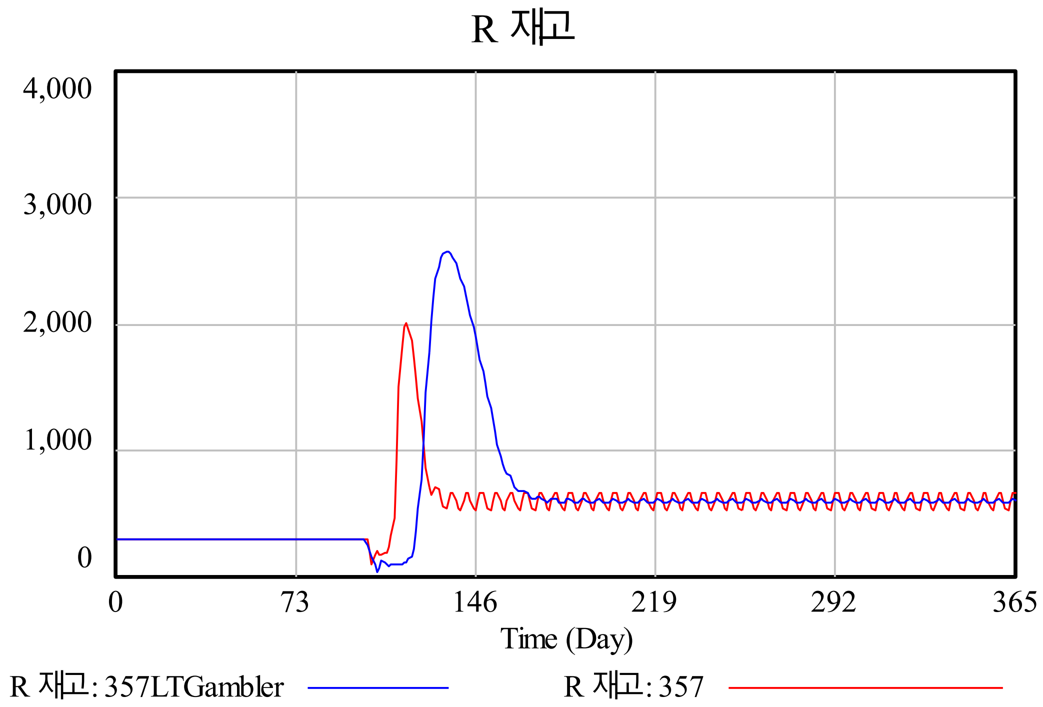
S Perceived lead time mean = SMOOTH (S lead time, S predicted period)

S Lead Time Forecast = 2*S Perceived Lead TimeAverage-S Lead Time

S Target Supply Line = S Quantity Forecast *S Lead Time Forecast

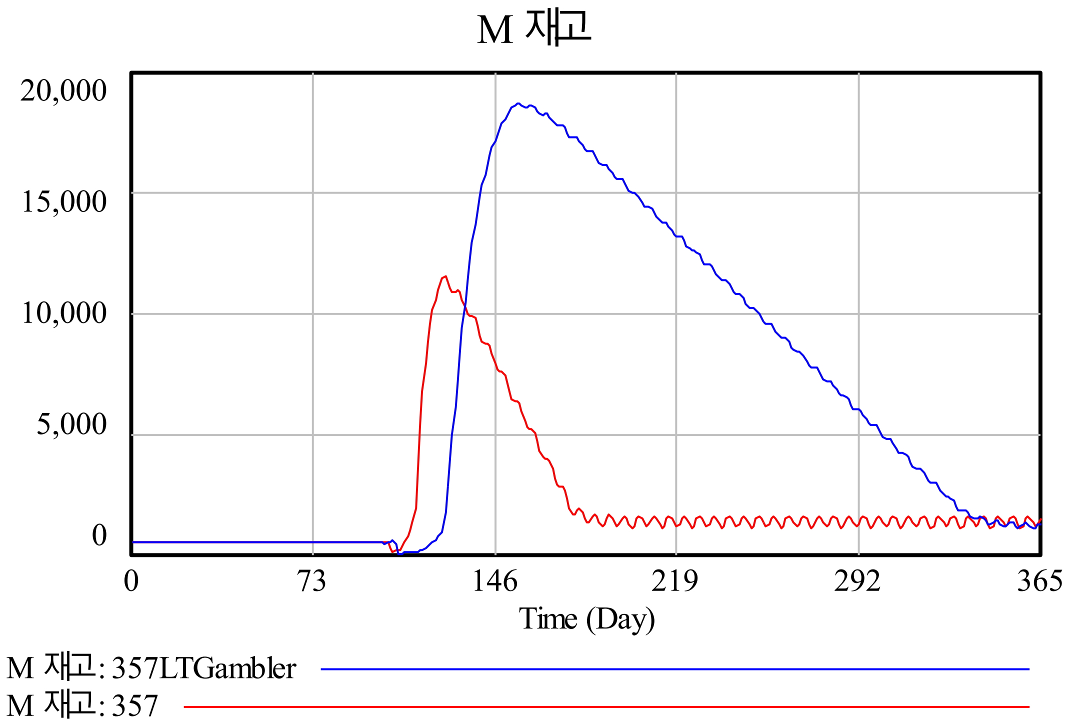
S Safety Level Days = S Lead Time Prediction

<Figure 5-17> R inventory comparison of 357 model and lead-time gambler heuristic model



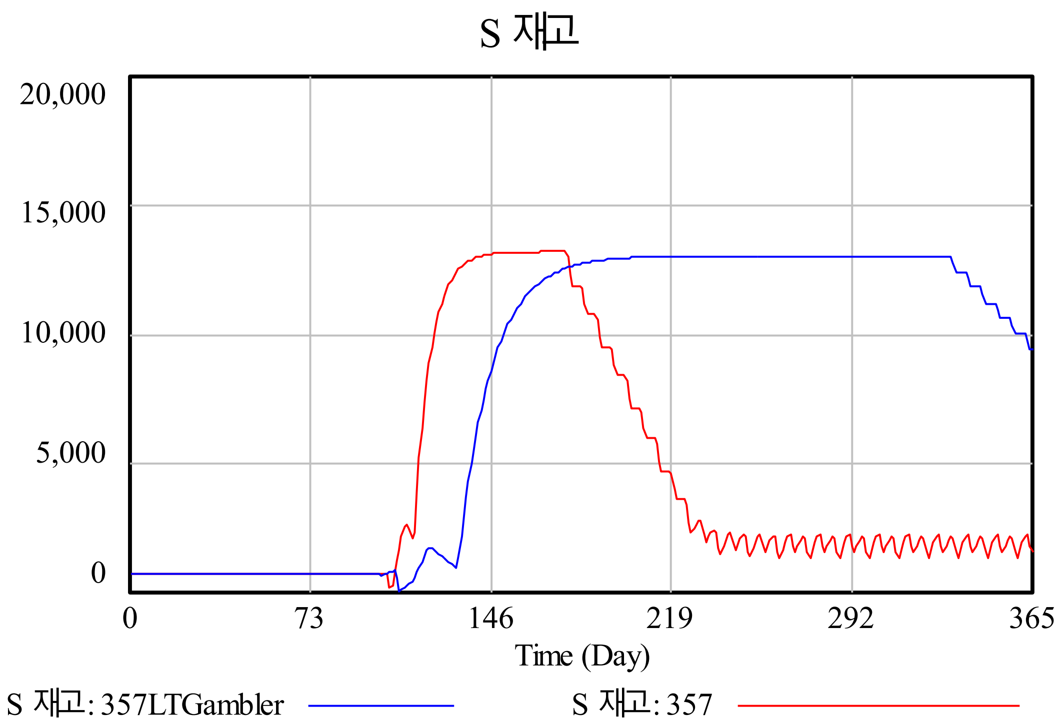
3 Compared to the57 model, the R inventory of the Gambler heuristic model shows a larger and longer overshoot, which also differs in average inventory. It is 613.03 compared to 538.84, indicating that it holds more than 10% more inventory.

<Figure 5-18> M inventory comparison between 357 model and lead time gambler heuristic model



When the gambler heuristic kicks in, M inventory also increases dramatically.

<Figure 5-18> S inventory comparison between 357 model and lead time gambler heuristic model



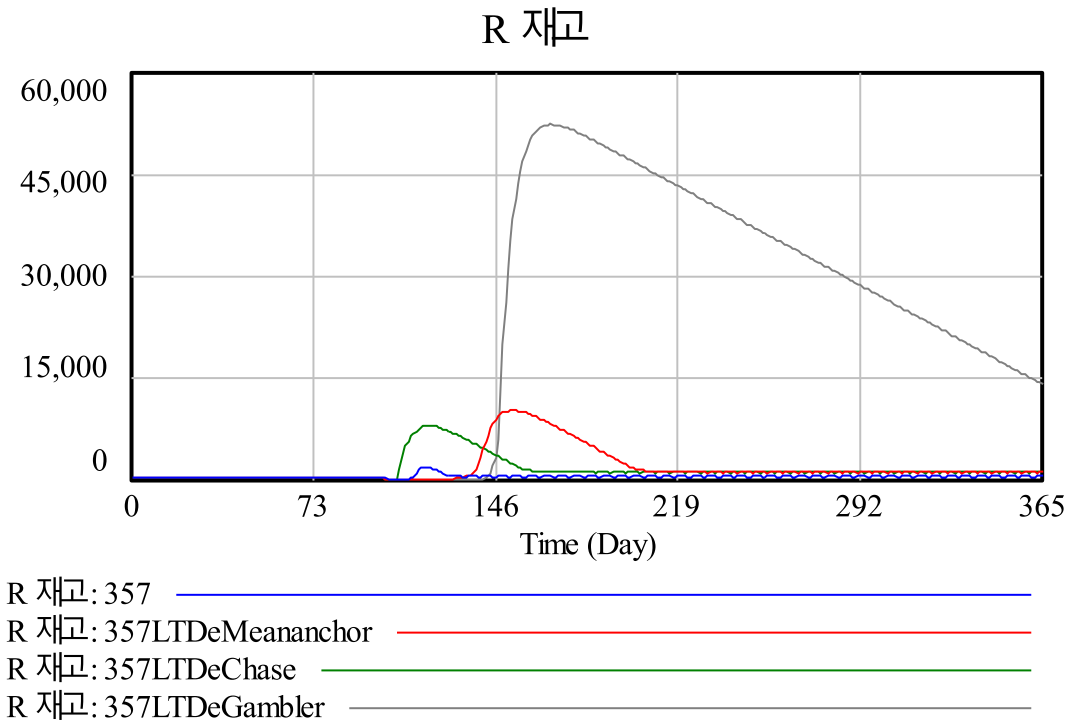
3 Compared to the57 model, the S stock of the Gambler model increases. But it's not as big as demand.

Average adherence to heuristics for lead time outperforms other heuristics. In the case of mean sticking, it means that it responds more slowly, which is presumed to play a role in reducing the whip effect. Both the following heuristic and the gambler heuristic caused the whip effect and performed worse than the base model.

3) When demand and lead time heuristics occur at the same time

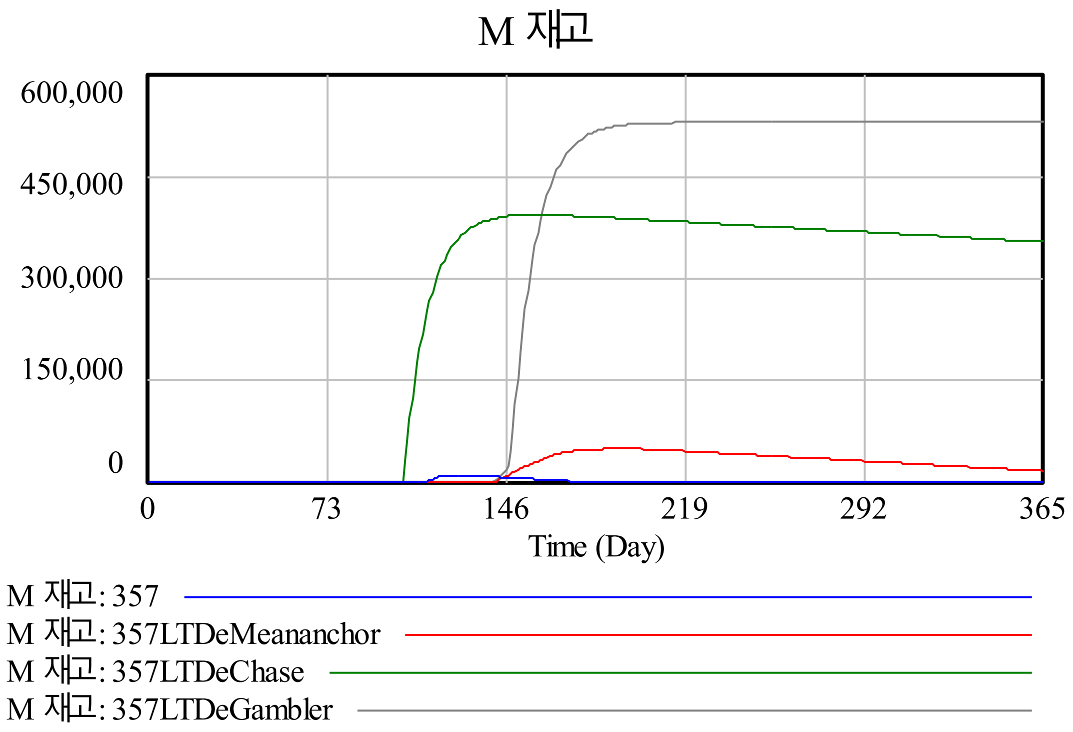
When demand increases from 101 to 200, and each lead time doubles from 101 days, look at when average sticking, following, and gambler heuristics occur simultaneously for both demand and lead time. The formula can include all of the formulas in the previous section.

<Figure 5-20> R inventory changes when three heuristics act on demand and lead time

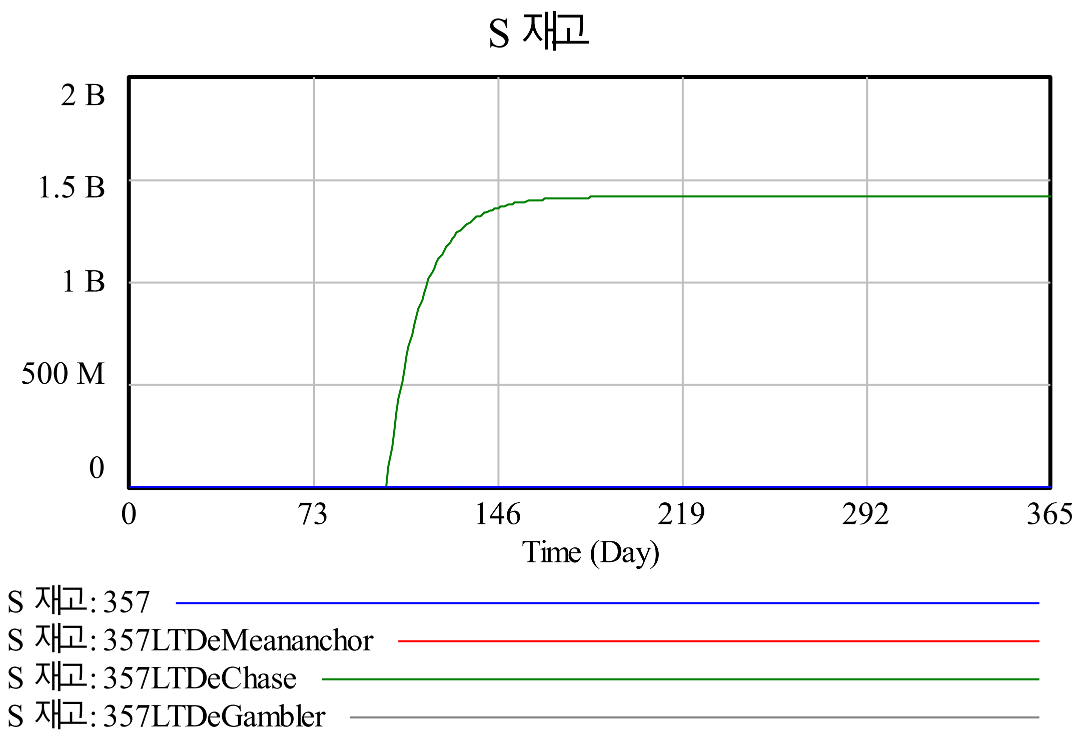


In R inventory, the following heuristic has been shown to cause an exceptionally large number of inventories.

<Figure 5-21> M Inventory Changes When Three Heuristics Act on Demand and Lead Time



<Figure 5-21> S inventory changes when three heuristics act on demand and lead time



Both M and S stocks show such large values that the following heuristics are incomparable.

<Table 5-3> Inventory comparison of basic model 357 and three heuristic models

model	S Stock	M Stock	R Stock	Supply Chain Benefits
357LT	115,651	38,402	1,365	-11,326
Average sticking	8,830	21,587	1,811	4,693
Following	969M	260,474	1,524	-136M
Gambler	406,815	302,154	20,751	-134,938

3The 57LT model reflects a doubling of the lead time from 101 days for the 357 model. Since demand and lead times have doubled at a certain point, comparisons with other heuristic models are possible. In the case of the average sticking heuristic, the R stock increased compared to the 357LT model, but the M and S stocks decreased. Supply chain profits were also the only positive.

Since the following heuristic has the worst consequences, it is judged to be a heuristic that should be avoided in the supply chain. The gambler heuristic is also better than the following heuristic, but the whip effect has appeared, and the inventory of M and S has increased significantly.

Chapter 6

Sector Optimization and Global Optimization Models

Local vs. global optimization in the Supply Chain

The interests of supply chain participants often conflict. Efforts to maximize one's own profits or minimize costs can hinder the optimization of other participants and eventually lead to a distance from global optimization.

As a supply chain, the problem of double margin is an essential phenomenon. For global optimization, someone has to sacrifice in the short term. If the quantity of demand is in a state of infinite growth, each person's sacrifice may end in a short period of time, but infinite growth cannot be controlled.

Will you increase customer service by inventory? Will you minimize costs by reducing inventory? Will you maximize ultimate profit? Supply chain participants' desired goals may vary. Aside from whether it is possible to coordinate these goals into one, it is necessary to virtually experience how to pursue them through simulation.

1) The problem of double margin

First, there is a supply chain. There are many stages in the supply chain, but here we consider them as one.

<Figure 6-1> Margin structure in the supply chain

This supply chain is purchased for $20 and sold for $80. The margins are high. To calculate the right amount of inventory to maximize profits, follow the following inventory importance.

Since the underage cost is $60 and the overage cost is $20 (assuming you sell and dispose of what's left over at 0 won), the inventory importance is 0.75 by U/(U+O). If demand is evenly generated from 0 to 100, then having 75 is the amount of reserve (inventory) that maximizes profits.

However, suppose that the supply chain is differentiated and there are 3 participants as shown in the following <Figure 6-2>.

<Figure 6-2> Margin structure of a supply chain consisting of three participants

Each has a margin of $20. But it's R who sells things. R must maintain adequate inventory. From R's point of view, U=$20 and O=$60. Therefore, the stock importance of R is 20/(60+20) = 0.25. That is, R is advantageous to have 25 inventories that meet only 25% of the demand from 0 to 100. There's a 75% chance that a customer will visit R and can't buy because it's out of stock.

If the supply chain is analyzed as one, the service rate to customers is high, while if it is split, the service rate will inevitably fall. This is because the margin structure is different. In order to increase their own profits, S and M must provide R with something extra so that R can take more stock. It is assumed that the only means S and M can control is to lower their margins. It is assumed that the demand has the form of STEP seen so far.

2) Global Optimization Strategy

3In model 57, the constants 3 (R), 5 (M), and 7 (S) were entered to indicate that the safety level of days = lead time. It was then stored as 357b.mdl. The only things a supply chain participant can do to achieve their goals is the number of days at the safety level and the unit selling price they offer downstream.

Controllable variables from the point of view of S: S safety level days, S unit selling price

Controllable variables from M's point of view: M safety level days, M unit selling price

Controllable variable from R's point of view: R safety level number of days

The range of days at the safety level was limited to 1 to 20. The selling price in S units was limited to equal to or greater than the S purchase cost and less than or equal to the selling price in M units.

10 <= S unit selling price <= 40

20 <= S unit selling price <= 60

The optimal values of the five controllable variables that maximize supply chain profits are derived through Bensim's optimization function.

S Safety Level Days = 1.4196575

Selling price in S = 10

M Safety Level Days =1.006375

Selling price in M units = 20

R safe number of days = 1.0008475

< Table 6-1> Results of maximizing overall supply chain profits

	357	357Total Eight
R Stock	538.84	203.49
M Stock	2,130	726.88
S Stock	4,068	507.26
R Gross profit	6,624	10,242
M Gross Profit	2,939	1,629
S Gross profit	1,307	-71.37
Supply Chain Benefits	10,872	11,800

Since it was an arbitrarily determined constant (3, 5, 7) in 3 57, the result of the overall optimization model has much less inventory. Overall supply chain profit was 11,800 for 3 57Total Opt, an increase of about 9% compared to the 357 model. Since R's profit has increased dramatically, it will be possible to share it with M or S. However, in reality, M or S have no choice but to choose a strategy that can guarantee their own interests. Therefore, policies that maximize overall supply chain profits are very likely to fail.

3) Local optimization strategy by order

Suppose that S does not have the ability to control the control variables of R or M. Then you'll try to optimize within the limits of what you can. S adjusts the number of days of the S safety level and the selling price of S units to perform optimizations that maximize the gross profit of S. The selling price of S units is limited to between $10 and $20. It may be possible to negotiate with M to make adjustments, but it is not easy. Since it is self-evident that the higher the unit selling price, the higher the gross profit, in the end it is equivalent to an optimization that sets the number of days of safety. As a result of the simulation, S safety level days = 1, S unit selling price = 20. Due to the large inventory burden, if there is almost no shortage of inventory, it is natural to have less inventory.

As a result,

S Safety Level Days =1

S unit selling price =20

S Gross income = 1,649

Optimization can also be carried out from M's point of view. Variables related to R and S are left as they are in the 357 model and optimized only for those that are within their control.

M Safety Level Days =1.13116

M unit selling price =40

M Gross income = 3,243

From R's point of view, it is assumed that only the R safety level can be adjusted. It is possible to lower the unit selling price, but this will increase demand by other invisible hands. Since it is not possible to predict how much it will increase, we do not assume the increase in sales volume here.

R Safety level days =1

R gross income = 6,773

The optimization results based on their own order are re-entered into the model and looked at how much supply chain benefit is generated.

S Safety Level Days =1

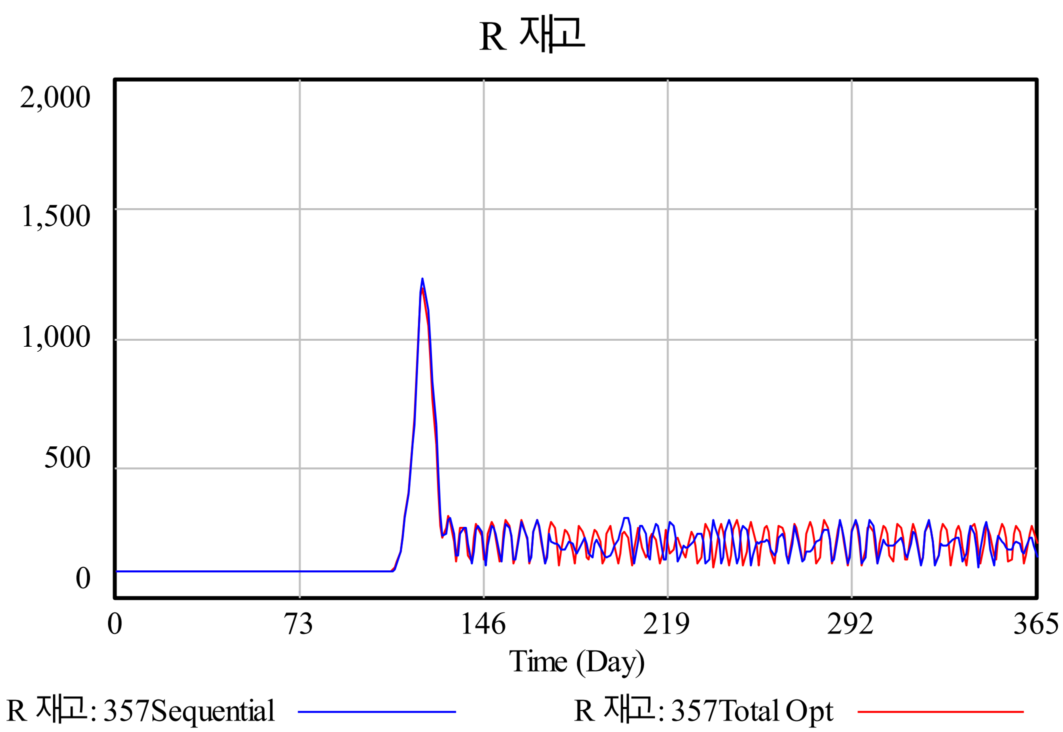
M Safety Level Days =1.13116

R Safety level days =1

< Table 6-2> Results of Maximizing Overall Supply Chain Profits

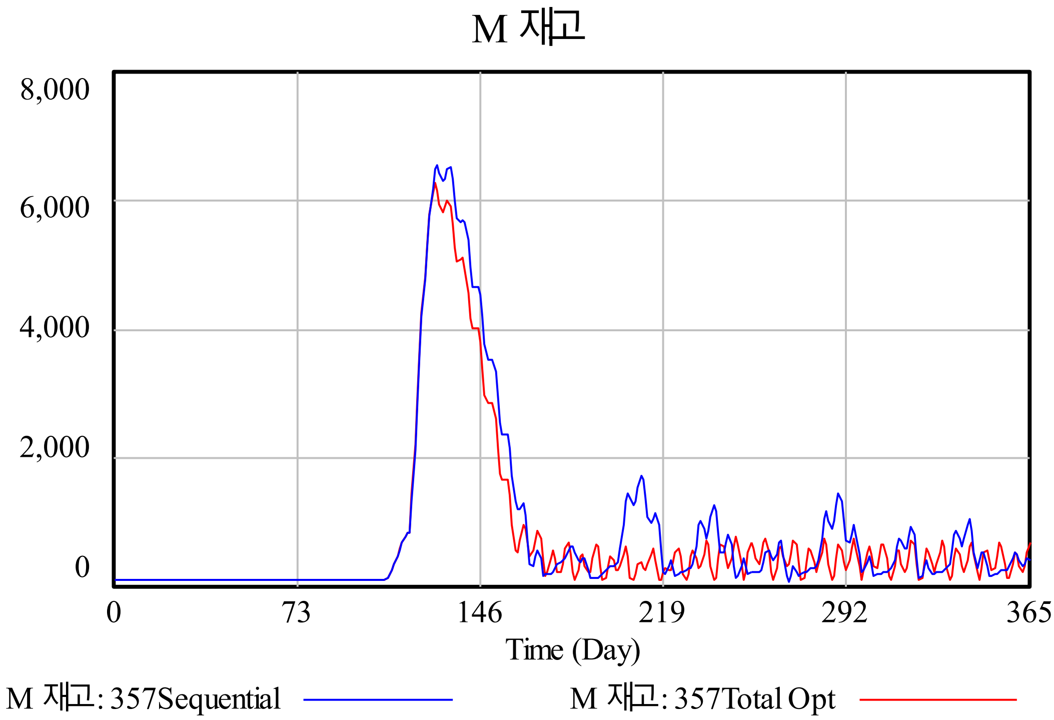
	357Sequential	357Total Eight
R Stock	201.46	203.49
M Stock	853.09	726.88
S Stock	284.52	507.26
R Gross profit	6,728	10,242
M Gross Profit	3,252	1,629
S Gross profit	1,639	-71.37
Supply Chain Benefits	11,620	11,800

<Figure 6-3> R inventory comparison for sequential optimization integration optimization



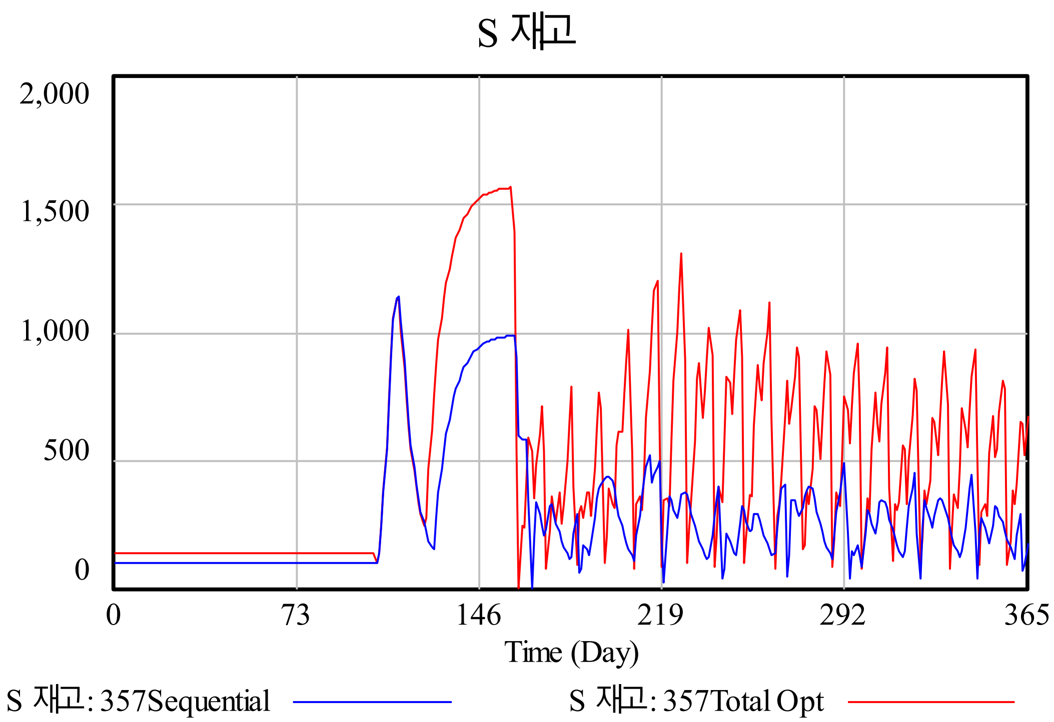
It was 201.46 for sequential and 203.49 for consolidation, showing roughly the same inventory levels. The size of the overshoot is also similar.

<Figure 6-4> Comparison of M inventory for sequential optimization integration optimization



853.03 vs. 726.88, the sequential optimization showed more M inventory.

<Figure 6-5> Sequential Optimization S inventory comparison for integrated optimization



For sequential optimization, it showed a mean S inventory of 284.52, and for integrated optimization , it was 507.26, indicating that sequential optimization had much less inventory. In the case of integration optimization, it was analyzed to increase the inventory of S to increase overall supply chain profits.

4) Strategies for maximizing service fulfillment

To maximize service fulfillment, inventory shortages must be minimized. You can adjust the number of days at the safety level in the 357 model. Use Bensim's optimization function. The optimization method uses the method Multiple Start = Random.

Generating a random number on the R demand increases the simulation time. This is because we need to look at all the possible impacts on these stores in the distribution of demand. Set the number of safe days to 3, 5, and 7 constants for the 357 model. It is necessary to break with the lead time.

Safety level days Run the simulation with three variables. Even if R's inventory drops a little, if M's inventory is high, R inventory shortage may be zero. Therefore, there may be several combinations of safety levels. In other words, multiple optimal solutions can be derived.

One of the best solutions is as follows.

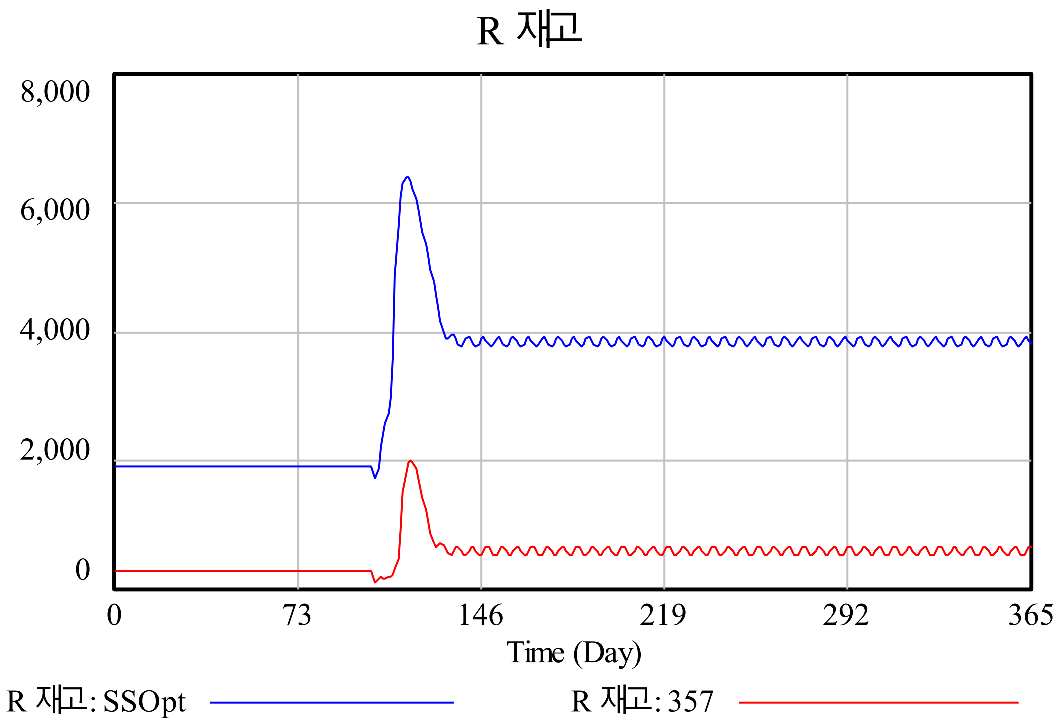
R safe level days = 19.212941

M Safe Level Days = 16.627939

S Safety Level Days = 13.882862

The R inventory of the model (SSopt) with these parameter values is as follows.

<Figure 6-6> R inventory changes when minimizing R shortage (SSopt) and model 357



It can be seen that R inventory is maintained at very high values. The case where the objective function, R inventory, is the lowest is 0, and the parameter combination in which R inventory is zero by applying any random number to the parameter is infinite. Therefore, the objective function should not be simply expressed as R stock shortage.

In the Optimization Setup window of Bensim, enter the following in the Payoff Elements field:

R Out of stock/-1

R Stock/-0.0000001

M in stock/-0.0000001

S in stock/-0.0000001

The number behind indicates weight. If it is positive, it is maximized, and if it is negative, it is minimized. It is a command to minimize R inventory shortages while at the same time minimizing R inventory, M inventory, and S inventory. Here, set the weight of the shortage very large compared to the weight of the inventory. This minimizes R shortages while at the same time informing you of the number of days at which each inventory has the lowest safety level. The simulation results give the following results:

R safety level days= 4.1000204

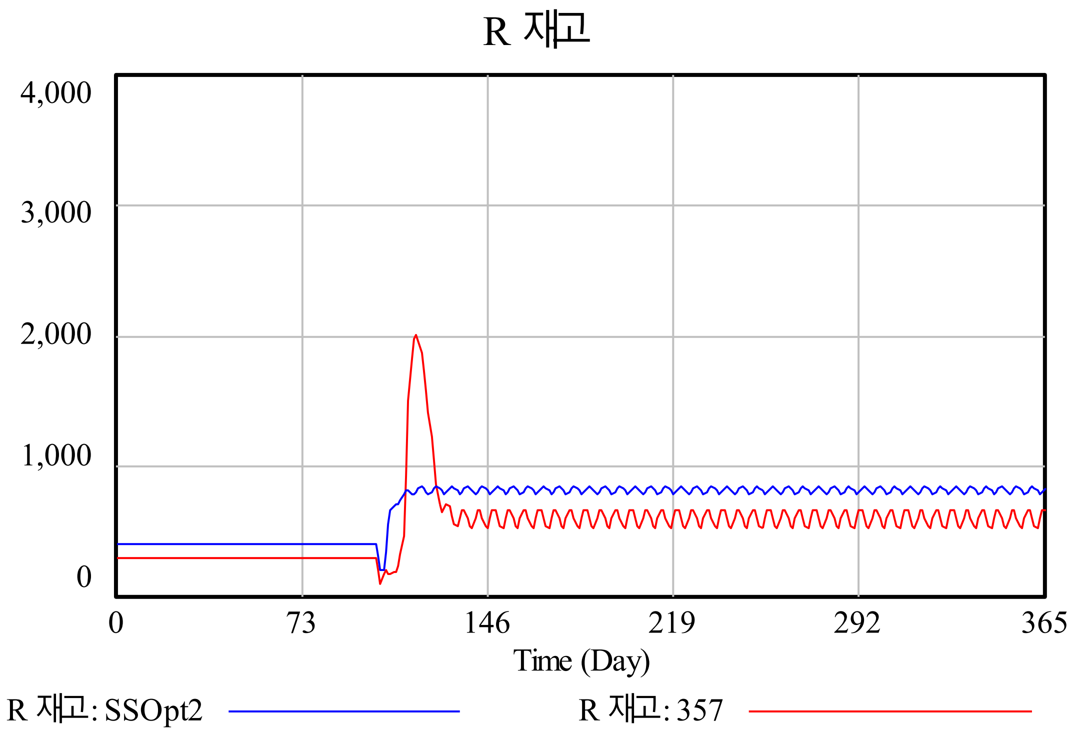
M Safe Level Days=13.454213

S Safety level days=1

The payoff value is -0.20432792. The preceding positive integer (0) means that the inventory shortage is zero, and the lower part is the sum of the inventory multiplied by the weight.

The file that minimized R by weighting the shortage and each inventory was named SSopt2.

<Figure 6-7> R inventory when minimizing R shortage while simultaneously minimizing each inventory



If you look carefully at the blue line in <Figure 6-7>, it approaches zero, but does not become zero. R Looking at the stock shortage, there was not a single stock shortage. If any of the three safety level days variables selected above are entered to a lower value, the R shortage will generate a positive number. In other words, R found the value with the lowest inventory level while minimizing the shortage. The average R inventory value of the 357 model is 538.84, which has increased considerably to 695.88 after optimization. The overshoot is smaller, but this is because the high level of safety level days lasts from 1 02 to 365 days to prevent inventory shortages on 1 01.

M Understocks and S stockouts were not taken into account. So the inventory shortage of these two things is quite large. However, since it is stored in white green and delivered after a certain time, it cannot be considered a loss of sales opportunity. End-users are also recorded as backlogs to meet demand, but when there is a shortage of inventory, delays occur, which can lead to things like customer churn. And if the user is a combatant, the conduct of the war itself can be difficult. On the other hand, the shortage of inventory located in the middle is not related to direct combat. When making optimizations, it is necessary to select the objective function according to the modeler's intention.

Even relatively simple R demand quantities and lead times require considerable time in simulation. However, if these variables contain relations with a normal distribution, more simulation time is required. This is because you don't know what random numbers will appear. Care must be taken when using it.

Chapter 7

Supply Contracts and Decoupling Strategies

Supply Contract and Decoupling Strategy

1) Effects of Revenue Sharing Agreements

Retailers at the end of the supply chain have less inventory if their margins are low. This leads to lost sales, which in turn leads to a decrease in profits throughout the supply chain. To prevent this, participants upstream in the supply chain should make concessions on their margins so that retailers have more inventory. Revenue-sharing agreements are a prime example of such a device.

However, when making a revenue-sharing contract, how to distribute revenue is a very important decision. It is also far-fetched to suggest that three people participated. In such cases, simulation can be used to resolve some disputes.

Based on the expected demand of the product, the simulation model is created in the traditional way. Suppose the 357 model is a representation of the existing business process.

The demand is represented by the STEP function that changes from 100 to 200, and there are three participants, R, M, and S, with lead times of 3, 5, and 7 days, respectively. It is assumed that the prediction method also uses the SMOOTH function. In the forecast , it is assumed that the forecast period is still applying the lead time.

S buys raw materials for $10 and sells them to M for $20. M sells back to R for $40. R sells for $80. In the margin structure, R has the highest margin rate. Since the number of R is generally more than the number of M, it can be said to be feasible in reality.

If you simulate a year in this state, there will be ups and downs, but the following < profit will occur as shown in Table 7-1>.

Table 7-1> < Profit in the Revenue Sharing Reference Model 357

	R Gross profit	M Gross Profit	S Gross profit	Supply Chain Benefits
Reference model (357)	6,624	2,939	1,307	10,872
specific gravity	61%	27%	12%	100%

Create a second model. To solve the problem of double margin, change the selling price of S units to $10, and change the selling price of M units to $10. Save with revenue sharing contract model 357 P S and perform simulation. All other variables are the same, only some adjustments were made to the selling price parameters. And maximize supply chain profits by adjusting the number of days at the safety level.

R safety level days = 1.17241

M Safety Level Days = 1.0043

S Safety Level Days = 1.00862

When it is, supply chain profits are shown to be maximized. Multiple answers were derived, and one of them was chosen.

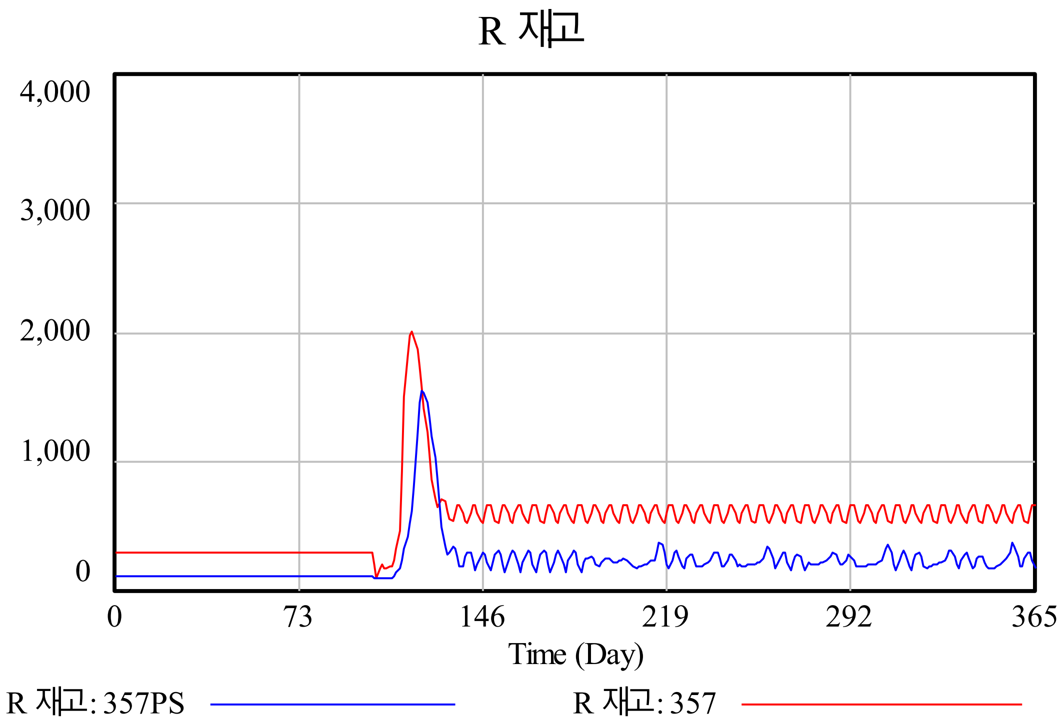
<Table 7-2> Supply Chain Benefits When Optimizing After Adjusting Selling Prices

	R Gross profit	M Gross Profit	S Gross profit	Supply Chain Benefits
Reference model (357)	6,624	2,939	1,307	10,872
specific gravity	61%	27%	12%	100%
357PS	7,230	3,200	1,422	11,852

By adjusting the selling price and the number of days at the safety level, R can earn $7,230 more, higher than $6,624 for the same demand. M and S also improve profits by about 10% in the revenue-sharing contract model compared to the 357 model. Win-win conditions were created through simulation.

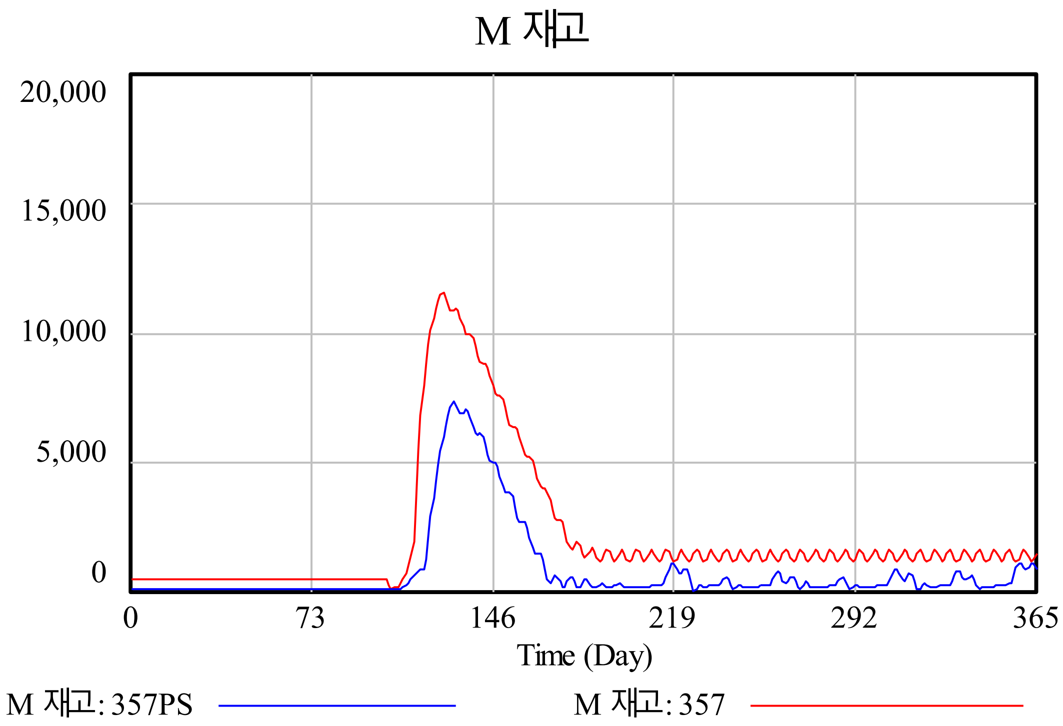
This is when we look at inventory and performance in the supply chain.

<Figure 7-1> R inventory comparison between independent operation (357 model) and integrated operation by revenue sharing (357PS)



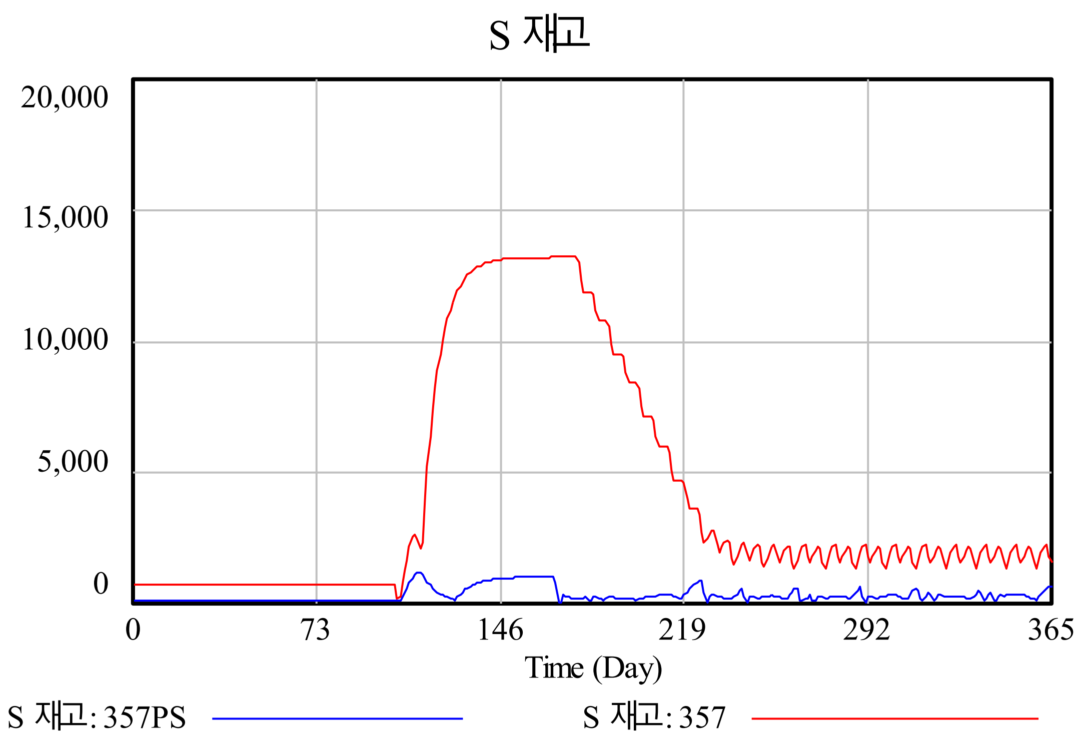
357 R stock average is 538.84, 357PS is 233.37. Inventory savings of more than 5 0% were achieved. In the case of the 357PS, inventory savings were achieved, but there was an average inventory shortage of 34.84 per day . For 357, it averaged 3.098 per day, a more than tenfold increase. This means that even if the shortage of inventory increases more than 10 times, the cost reduction effect due to inventory is great. The cost of a one-day inventory shortage is set twice as high as the cost of maintaining inventory. I vaguely think that there should not be an inventory shortage, but it depends on the margin structure. Sometimes moderate shortages help improve overall profits.

<Figure 7-2> M inventory comparison between independent operation (357 model) and integrated operation by revenue sharing (357PS)



The average of M stocks dropped from 2,130 to 850.80 for 357PS. The size of the overshoot has also been reduced. M In terms of stock shortage, the 357 model is 34.61 and the 357PS is 133.30. Supply chain profit reflects M inventory shortfalls. However, M's inventory shortage is not directly related to the overall benefit of the supply chain. However, it was reflected because M can carry out special management on the shortage of inventory. Without special management, supply chain profits are greater. Since its value does not increase, it is omitted here.

<Figure 7-3> S inventory comparison between independent operation (357 model) and integrated operation by revenue sharing (357PS)



The average daily value of the S inventory of the 357 model was 4,068. In the case of the model (357PS) after a series of improvement activities such as a revenue sharing contract, the daily average is only 313.93. Moreover, the highest amount (directly related to storage capacity) decreased by more than 90%, from 13,209 to 1,208. It is a benefit that can only be enjoyed in cooperative supply chains, such as signing a revenue-sharing agreement. If it had been run independently, would S have been able to reduce the number of safe days? Not at all.

Therefore, cooperative integrated operations can not only increase profits but also improve management costs. These improvements in administrative costs may be far greater than the increase in supply chain profits.

Of course, there are also points to be careful about for cooperative supply chain operations such as revenue-sharing contracts. In particular, systems must be put in place to prevent opportunism. From R's point of view, if you make a no-data transaction and treat it as a loss, you can make a significant profit. All sales must be made by POS, etc., and losses must be managed transparently. Only then can the cooperative relationship be maintained. The timing of revenue allocation is also important. Since R earns money first and distributes it later, even if you delay the time of distribution, you can increase profits from interest, etc. This leads to a decrease in profits for M or

S. This should also be complemented by a transparent accounting system.

Although integrated operations are far superior to individual operations, these shortcomings are not well utilized in practice. It's a shame.

2) Decoupling Strategy

So far, the volume of demand has undergone a major change in 101 days. It changed drastically from 100 to 200. But what should we do if we anticipate such a catastrophic event? There is no need to leave a whiplash effect occurring, a sudden change, and then an increase in inventory. Inventory is called a nticipation inventory, which can be held separately by one of the participants in the supply chain and released in the event of a sudden change to prevent the supply chain from being disrupted. This is called a decoupling strategy.

Who? How long? Whether you will have it is a question. It's kind of like putting a bell on a cat's neck. In integrated/cooperative supply chain operations, it is possible to put a drop.

(1) Who will hold the expected inventory?

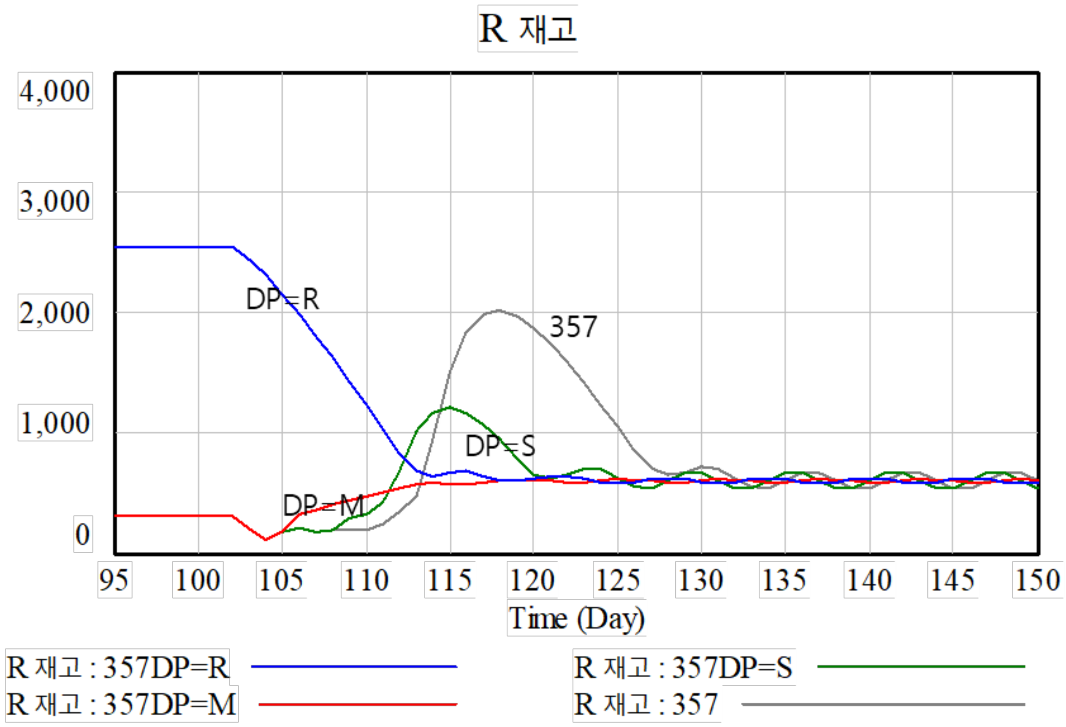
Modify some of the 357 models. Include the expected inventory in each target safety level. Assuming you know the day of the sudden change, the estimated inventory is set to be reflected in the target safety level only from the beginning to 100 days and excluded from the next day. R, M, and S can all be candidates for the expected inventory. Using Bensim's optimization function, the number of DP days (expressed as multiplying the number of DP days in the required quantity forecast to calculate the expected inventory) is obtained and entered to determine the value that maximizes supply chain profits, and performance is measured. Select the best alternative.

When the decoupling point was set to R, the number of DP days = 22.4068 was derived.

When the decoupling point was set to M, the number of DP days = 7.19663 was derived.

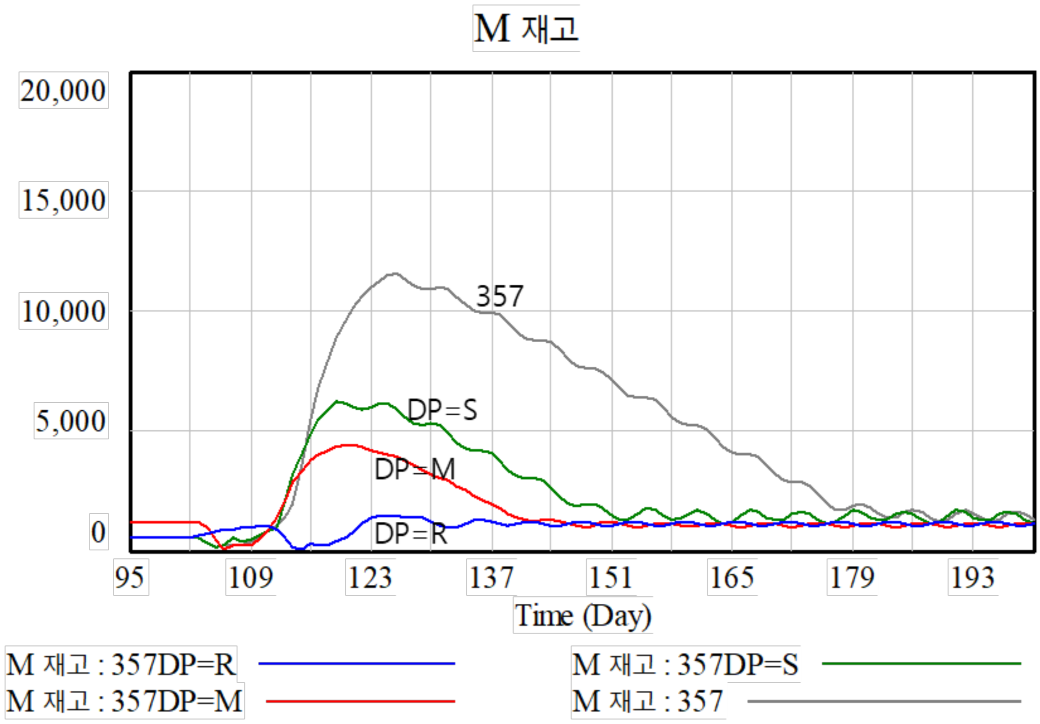
When the decoupling point was set to S, the number of DP days = 15.4607 was derived.

<Figure 7-4> R inventory according to decoupling point



If the decoupling point is at R, it is the blue line. It initially has more than 2,000 units in stock. And as a sudden change occurs, a state of equilibrium is achieved. When the decoupling point is at S, it is slightly closer to the 357 model, but it shows a stock behavior that causes less overshoot. The ideal is when the decoupling point is at M. Since R does not have the expected inventory, it has a thin inventory from the beginning, decreases slightly, and then immediately balances.

<Figure 7-5> M inventory according to decoupling point



DP=M, which uses M in the middle as the decoupling point, has the most inventory before 1 00 days. After a sudden change, it fell to zero and rebounded, holding more than 4,000 inventories before regaining equilibrium. An overshoot occurred. In the case of DP = S, it shows a greater overshoot than DP = M, and the equilibrium point after 1 50 days is also higher than other alternatives. That causes a lot of M inventory. DP=R, on the other hand, rarely overshoots, and finds the equilibrium point the fastest. In terms of M inventory, DP=R is judged to be the best.

<Figure 7-6>　S　inventory according to decoupling point

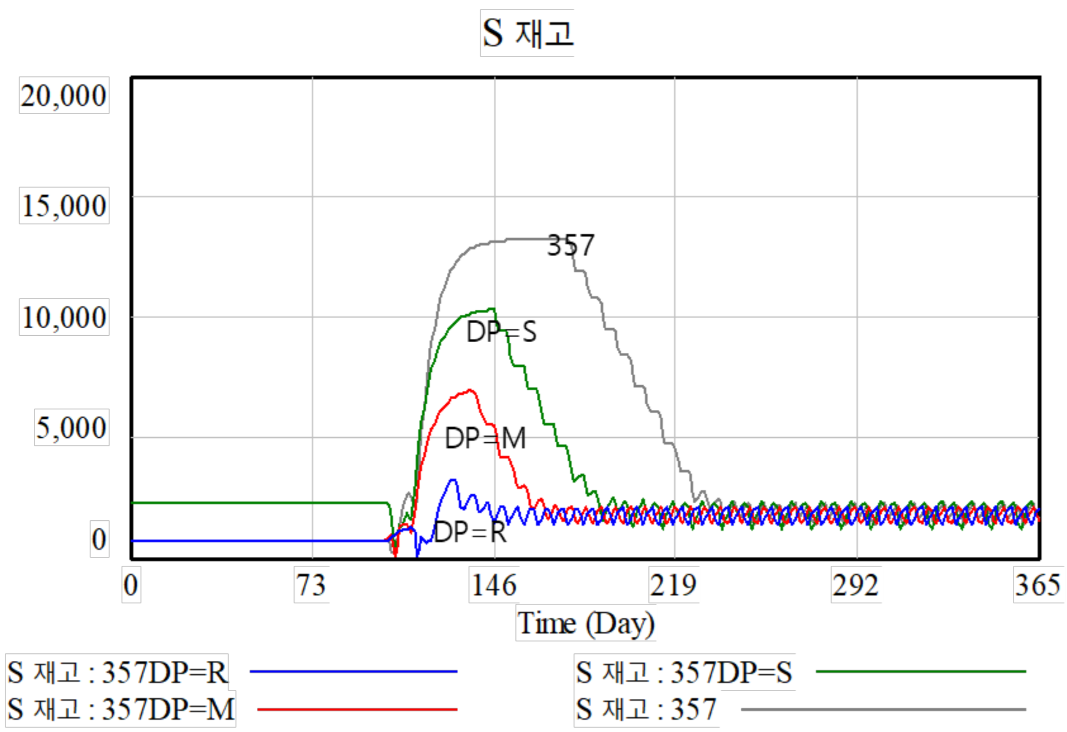


Table < 7-3> Decoupling Point　Inventory and Supply Chain Profits by Strategy

model	R Stock	M Stock	S Stock	Total Stock	Supply Chain Benefits
357	539	2,130	4,068	6,737	10,872
DP=S	516	1,413	3,072	5,001	11,193
DP=M	508	1,253	1,885	3,646	11,316
DP=R	1,176	916	1,453	3,545	11,222

The DP=R strategy has the least inventory. We　have the expected inventory where we need it, so we don't need to order and pick it up.　Nevertheless, in terms of supply chain profits, the DP=M strategy appears to be superior. This appears to be due to differences in　expected inventory, inventory shortages and margin structure.

The answer to who has the expected inventory when there is a big change is the second step.　In general, the decoupling point is the meeting point with the user or customer.　However, this branch (usually a retailer) does not have enough storage space. There　should be an analysis of more cases, but the fact that DP=M is better than or similar　to DP=R means that DP=M is acceptable.

(2) How much expected inventory should I have?

The amount of expected inventory held in case of sudden changes varies depending on the strategy. We estimated the following parameters for optimization :

DP=R → DP days=22.4068

DP=M → DP days=7.19663.

DP=S → DP days=15.4607

Accordingly, the estimated inventory was determined. Between 0 and 100 days, DP = R ranges from 500 to 2,540, with an expected inventory of 2,010. On the other hand, at DP=M, M had an estimated inventory of 919, from 300 to 1,219. The expected inventory DP=M was much smaller, which prepared for a sudden change. Of course, it can vary depending on the lead time or the size of the rapidly changing demand, so it is necessary to simulate more diverse cases.

< Table 7-4> What is the estimated inventory?

strategy	Estimated Inventory	Compared to the increased demand volume (100)
DP=R	2,010	20x
DP=M	919	9x
DP=S	1,546	15x

Finding OO matching to increased demand is due to generalization. Here, the amount of demand is changed from 100 to 200, and control will continue at the target safety level for the first 100. It will be easy to apply a value when considering lead time or the like for the increased demand 100.

Chapter 8

Shortfall Games

Shortage Games in the Supply Chain

Each echelon of the supply chain is networked because there are multiple participants. The most common structure is 1-2. It refers to the case where there is one supplier and two buyers. Because it expands from one to two, it is also called a divergent structure. The 2-1 structure is called a convergent structure because it comes together.

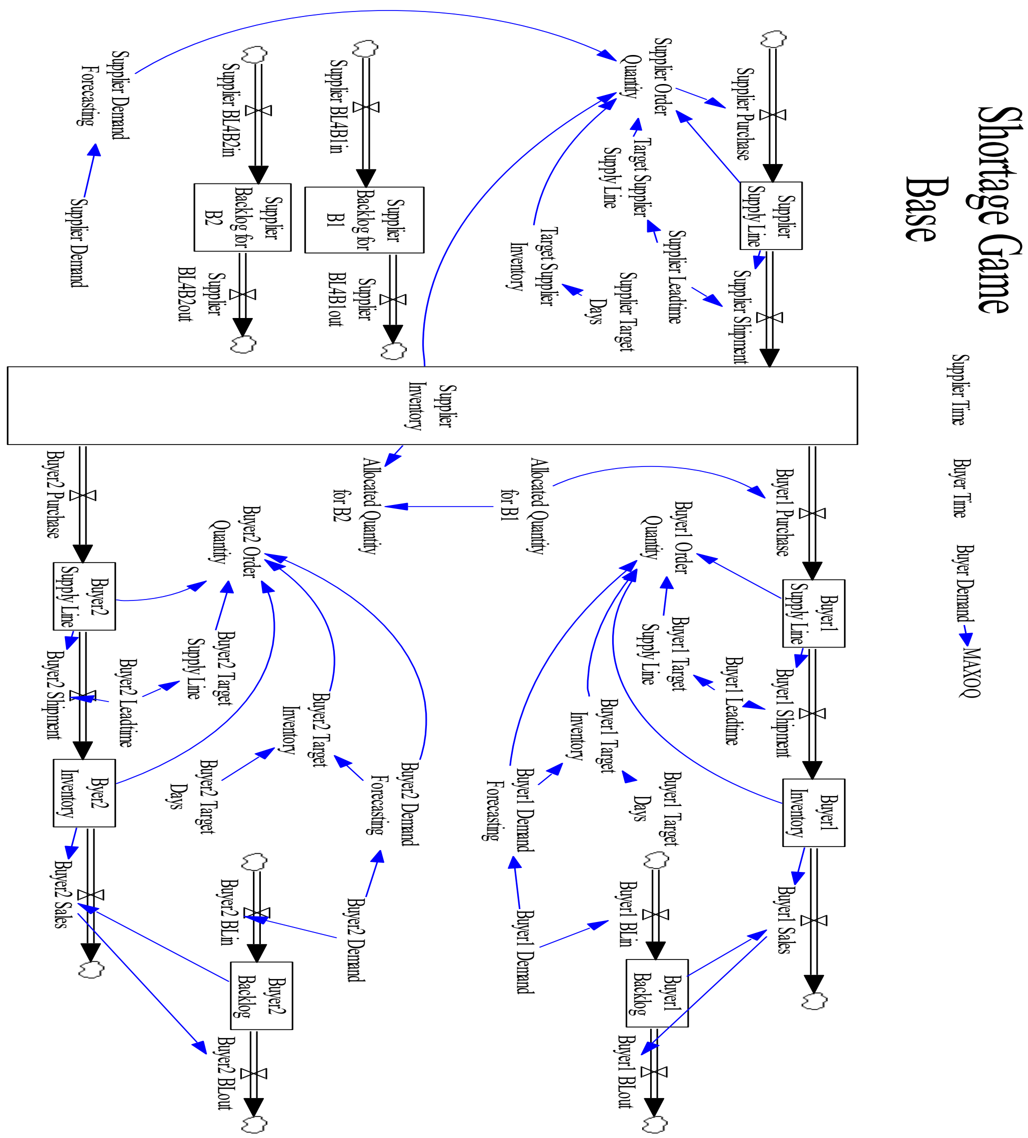
In a distributed structure, there is more competition, which creates strategies for more effective and efficient operations. A strategy is a plan for action. As part of the strategy, they create a shortfall game to get more inventory. Here, we try to identify the mechanism of why the shortage game occurs.

When the shortage game occurs, it doesn't cause a whiplash effect. The causes of the whip effect are varied. One of them is the shortage game. Reducing the shortfall game can reduce the whip effect. But you can't get rid of it.

1) 1-2 Supply Chain Model

Using the model discussed in the previous chapter, the 1-2 model was made as shown in the following <Figure 8-1>.

<Figure 8-1> 1-2 Supply Chain Model



<Figure 8-1> The relation used in the model is as follows.

Allocated Quantity for B1=MIN(Supplier Backlog for B1, Supplier Inventory*ZIDZ(Supplier Backlog for B1, Supplier Backlog for B1+Supplier Backlog for B2))

Allocated Quantity for B2=MIN(Supplier Inventory-Allocated Quantity for B1, MIN(Supplier Backlog for B2, Supplier Inventory*ZIDZ(Supplier Backlog for B2, Supplier Backlog for B1+Supplier Backlog for B2)))

Buyer Demand=100

Buyer Time=3

Buyer1 Backlog= INTEG (Buyer1 BLin-Buyer1 BLout, Buyer Demand)

Buyer1 BLin=Buyer1 Demand

Buyer1 BLout=Buyer1 Sales

Buyer1 Demand Forecasting=SMOOTH(Buyer1 Demand, Buyer Time)

Buyer1 Demand=Buyer Demand+STEP(Buyer Demand, 31)

Buyer1 Inventory= INTEG (Buyer1 Shipment-Buyer1 Sales,Buyer1 Target Inventory)

Buyer1 Leadtime=Buyer Time

Buyer1 Order Quantity= MIN(MAXOQ, MAX(0, Buyer1 Target Inventory+Buyer1 Target Supply Line-Buyer1 Inventory-Buyer1 Supply Line+ Buyer1 Demand Forecasting))

Buyer1 Purchase=Allocated Quantity for B1

Buyer1 Sales=MIN(Buyer1 Inventory, Buyer1 Backlog)

Buyer1 Shipment=Buyer1 Supply Line/Buyer1 Leadtime

Buyer1 Supply Line= INTEG (Buyer1 Purchase-Buyer1 Shipment,Buyer1 Target Supply Line)

Buyer1 Target Days=Buyer Time

Buyer1 Target Inventory= Buyer1 Demand Forecasting*Buyer1 Target Days

Buyer1 Target Supply Line=Buyer1 Demand Forecasting*Buyer1 Leadtime

Buyer2 Backlog= INTEG (Buyer2 BLin-Buyer2 BLout,Buyer Demand)

Buyer2 BLin=Buyer2 Demand

Buyer2 BLout=Buyer2 Sales

Buyer2 Demand Forecasting=SMOOTH(Buyer2 Demand, Buyer Time)

Buyer2 Demand=Buyer Demand+STEP(Buyer Demand, 31)

Buyer2 Leadtime=Buyer Time

Buyer2 Order Quantity=MIN(MAXOQ, MAX(0, Buyer2 Demand Forecasting+Buyer2 Target Supply Line+Buyer2 Target Inventory-Byer2 Inventory-Buyer2 Supply Line))

Buyer2 Purchase=Allocated Quantity for B2

Buyer2 Sales=MIN(Buyer2 Backlog, Byer2 Inventory)

Buyer2 Shipment=Buyer2 Supply Line/Buyer2 Leadtime

Buyer2 Supply Line= INTEG (Buyer2 Purchase-Buyer2 Shipment,Buyer2 Target Supply Line)

Buyer2 Target Days=Buyer Time

Buyer2 Target Inventory= Buyer2 Demand Forecasting*Buyer2 Target Days

Buyer2 Target Supply Line=Buyer2 Demand Forecasting*Buyer2 Leadtime

Byer2 Inventory= INTEG (Buyer2 Shipment-Buyer2 Sales,Buyer2 Target Inventory)

MAXOQ=Buyer Demand*10

Supplier Backlog for B1= INTEG (Supplier BL4B1in-Supplier BL4B1out,Buyer Demand)

Supplier Backlog for B2= INTEG (Supplier BL4B2in-Supplier BL4B2out,Buyer Demand)

Supplier BL4B1in=Buyer1 Order Quantity

Supplier BL4B1out=Buyer1 Purchase

Supplier BL4B2in=Buyer2 Order Quantity

Supplier BL4B2out=Buyer2 Purchase

Supplier Demand Forecasting=SMOOTH(Supplier Demand, Supplier Time)

Supplier Demand=Buyer1 Order Quantity+Buyer2 Order Quantity

Supplier Inventory= INTEG (Supplier Shipment-Buyer1 Purchase-Buyer2 Purchase,Target Supplier Inventory)

Supplier Leadtime=Supplier Time

Supplier Order Quantity= MAX(0, Target Supplier Inventory+Target Supplier Supply Line-Supplier Inventory-Supplier Supply Line+Supplier Demand Forecasting)

Supplier Purchase=Supplier Order Quantity

Supplier Shipment=Supplier Supply Line/Supplier Leadtime

Supplier Supply Line= INTEG (Supplier Purchase-Supplier Shipment,Target Supplier Supply Line)

Supplier Target Days=Supplier Time

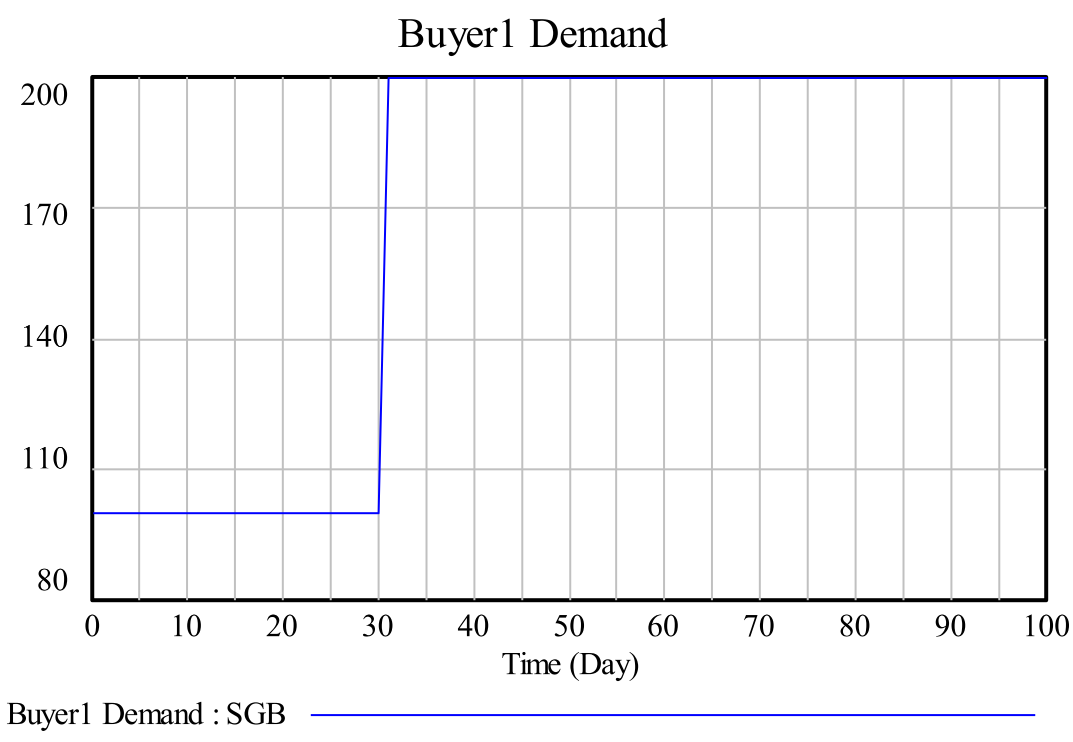
Supplier Time=5

Target Supplier Inventory=Supplier Demand Forecasting*Supplier Target Days

Target Supplier Supply Line=Supplier Demand Forecasting*Supplier Leadtime

There is one supplier, and there are two buyers. Each manages their own inventory. In order to cause a shortage situation, buyer demand (Buyer1 Demand and Buyer2 Demand) was set to Buyer Demand + STEP (Buyer Demand, 31). Demand from both buyers is not volatile except for 1 day. From days 0 to 30, there are 100 demands, and from days 31 to 100, 200 demands.

<Figure 8-2> Buyer Demand Patterns in Shortfall Game Models



Since the demand of the two buyers suddenly changed from 1 00 to 200 on the 31st, even if the supplier has its own safety stock, it causes a temporary shortage due to lead time. Routine volatility in demand generation was not taken into account.

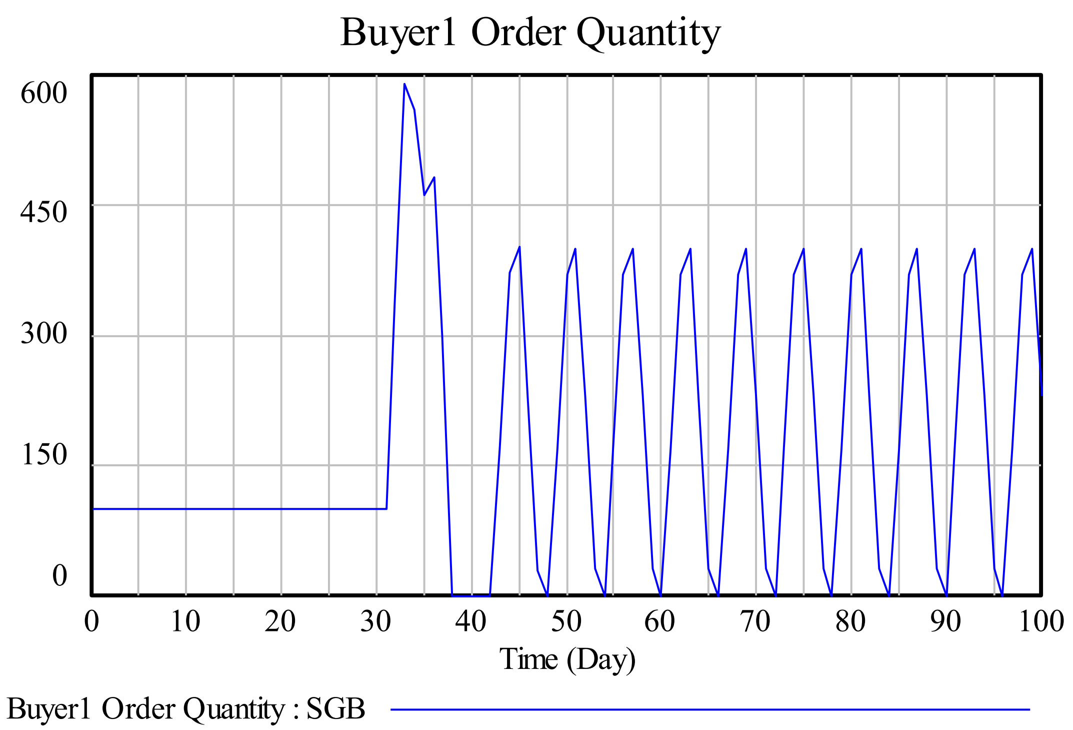
All participants in the supply chain manage backlogs. If a buyer places an order and is out of stock, the supplier gives the buyer as soon as stock becomes available. Buyers are also modeled to manage outstanding orders for end consumers.

The buyer set the forecast adjustment time to 3 days if a forecast was required, and the supplier set it to 5 days. That is, lead time or management time has constants. The buyer's target inventory level (Buyer1 Target Days) was the same 3 days. The same applies for target supply lines during lead times. The lead time for suppliers is 5 days. The buyer is on the 3rd and the supplier on the 5th.

If the order volume of two buyers increases at once, one supplier will run out of stock and must be allocated. The allocation rules were limited to proportional allocation. Proportional allocation is a method of allocation based on the order volume of two buyers. For example, a supplier has 150 units in stock, but one buyer orders 100 units, and two buyers order 200 units. Then, using proportional allocation, 50 units are offered to 1 buyer and 100 units to 2 buyers. This process is represented in Allocated Quantity for B1(B2) in <Figure 8-1>.

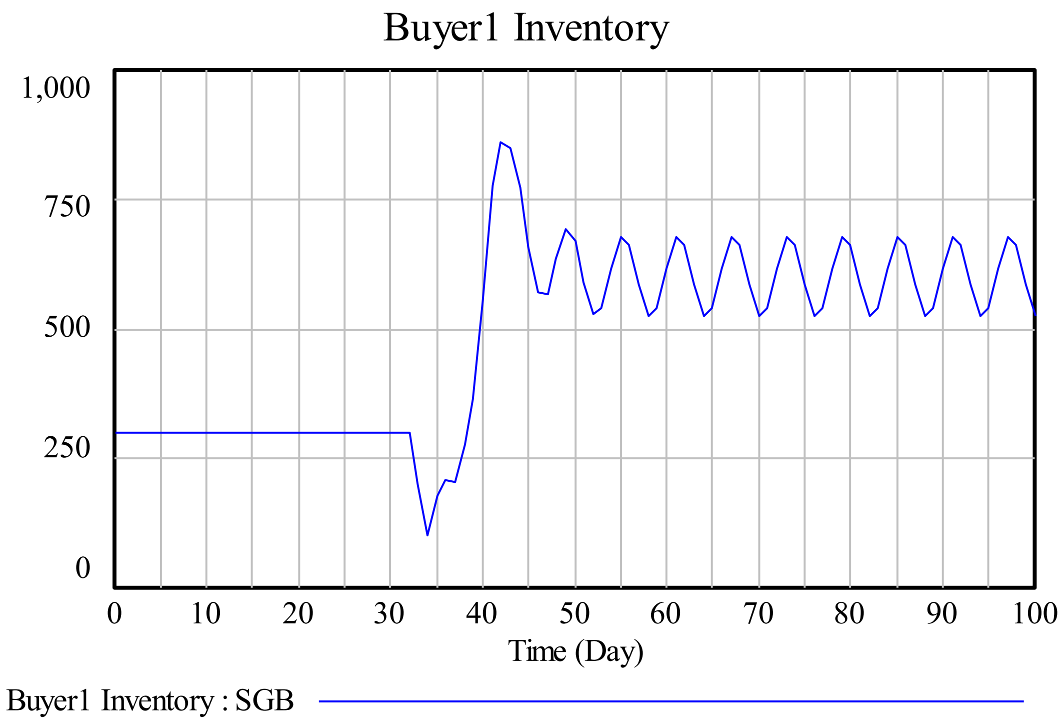
3 Afterthe 1st, there is a temporary shortage of inventory. The graph of the buyer's order volume for this period is shown in <Figure 8-3>.

<Figure 8-3> Buyer1 Order Quantity in Out of Stock



Buyer orders can increase by nearly 600 between 30 and 40 days. After 40 days, orders are increased, decreased, and repeated. However, since it is a wave within a certain range, the order volume can be said to have reached equilibrium. This is due to two negative loops for inventory and supply lines. It is the effect of lead time that causes waves. It was explained earlier that if there is a delay and a negative loop, it draws a wave.

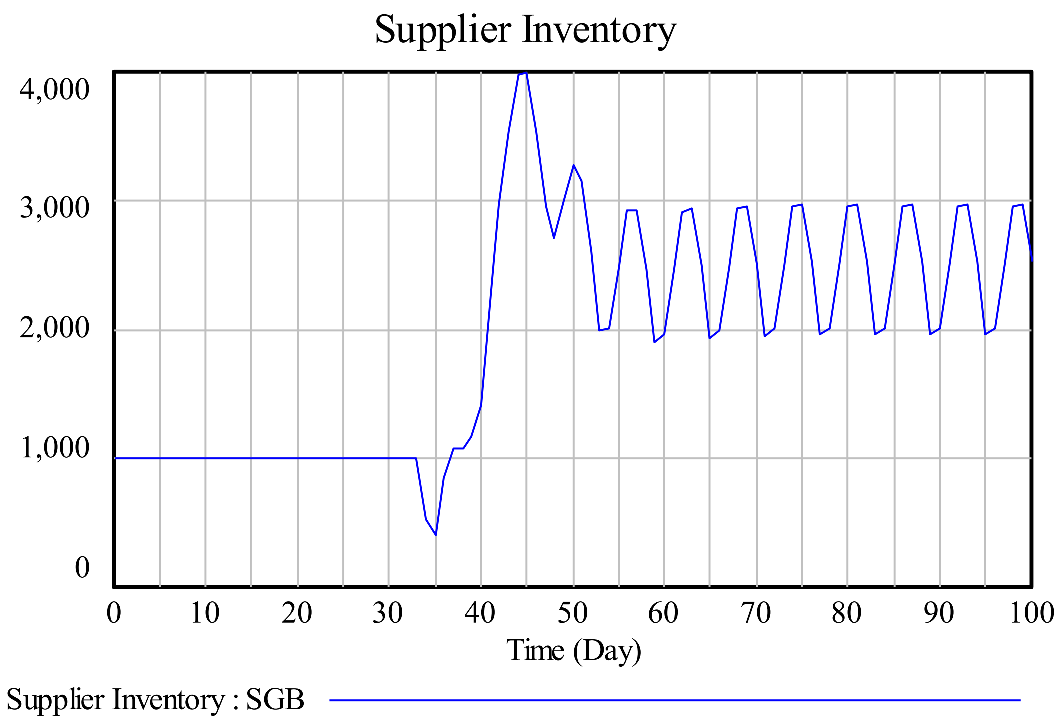
<Figure 8-4> Buyer inventory changes for models 1-2



Just because a buyer's inventory hasn't dropped to zero doesn't mean they haven't run out of stock. This phenomenon is due to the integral method for stock variables in system dynamics. This is because the stock value is calculated after the output goes out and the input comes in. It means that you give away today from the stock you had the day before, and then count the inventory you receive.

If you look at the buyer's inventory changes, you can see that the whip effect occurs. When switching from 300 inventory levels to 600, more than 800 inventories increase and then come down again. Other buyers see the same pattern.

<Figure 8-5> Supplier inventory changes in models 1-2



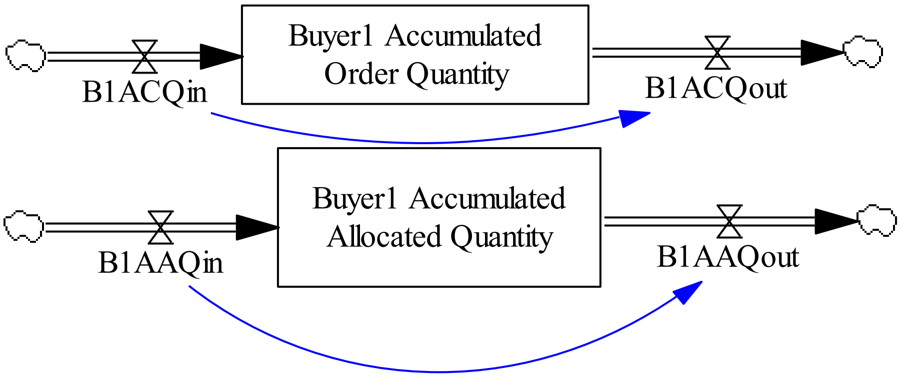
Supplier inventory averaged 1.954 and had a maximum of 3,993.

2) Implicit shortfall game occurrence

Buyers want to increase their order volume by adding in addition to the adjustments in inventory and supply lines in order to quickly get out of the shortage situation. This is called a shortage game. With no information about other buyers, and no information about how much inventory the supplier has, that buyer distorts the order volume based on the experience of the photo. Because it distorts itself, it is called the endogenous shortage game. The game of intrinsic shortage can be seen as a manifestation of a kind of opportunism.

Some of the models in < Figure 8-1> were changed to show opportunistic tendencies.

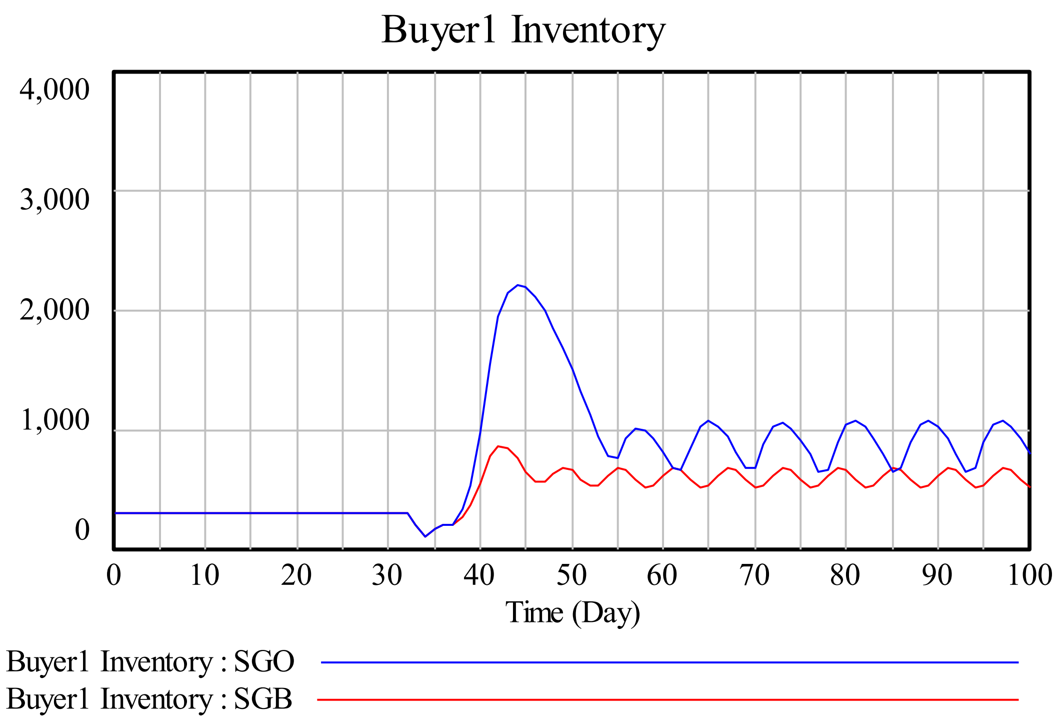
<Figure 8-6> Variables used to represent the cumulative shortfall in order volume and quota



The buyer stores the order quantity for 3 days, and the buyer stores the allocated amount for 3 days. Find the Buyer1 Shortage Ratio as Buyer1 Accumulated Allocated Quantity/Buyer1 Accumulated Order Quantity. Then, create a new variable called Buyer1 Prior Order Quantity and apply the relation of the existing Buyer1 Order Quantity. Instead, establish a relation called Buyer1 Order Quantity= Buyer1 Prior Order Quantity/Buyer Shortage Ratio. Do the same for buyer 2. After establishing this relation, name the simulation data file SGO and run it. The reason why the accumulation was done here for 3 days is because, as mentioned earlier, the buyer set all the beats on the 3rd.

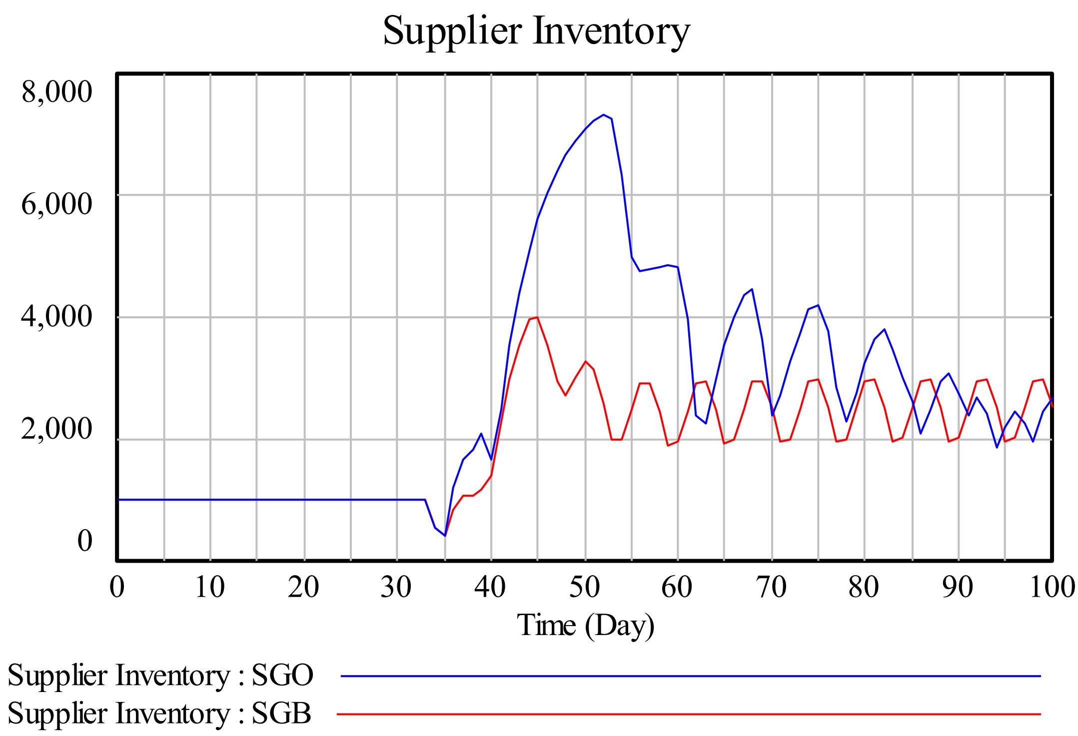
In the last 3 days, Buyer 1 has ordered 100 pieces and received only 50 pieces. The cumulative ratio is 300 to 150. The shortage rate is 0.5. If you need 100 units again today (Buyer1 Prior Order Quantity), you will order 200 units (Buyer1 Order Quantity), which is 100/0.5. At this time, too much should not be ordered per day, so a limit called MAXOQ was applied. Buyers could only order up to 1,000 units. And if the value of the Shortage Ratio is 0.000001, the order volume will be 1 million times. To prevent this, the shortfall rate was limited to 0.5 or more. The shortage rate can also have a value of 1 or more because of the backlog. In this case, the Buyer1 Order Quantity may be smaller than the Buyer1 Prior Order Quantity. This was also limited (1.5) to prevent excessive reduction.

<Figure 8-7> Implicit Shortfall Buyer inventory in a gaming situation



The game of implicit shortfall is applied to the blue mountains. It may have more than 2,000 items in stock. When an inventory shortage occurs, the shortfall game is prominent due to opportunistic tendencies, which generates a huge overshoot in the buyer's inventory . And if you look at the two lines that you see after 60 days, the amplitude of the blue line is greater. This is due to a delay in calculating the shortage rate. The greater the delay, the greater the vibration width.

<Figure 8-8> Implicit Shortfall Supplier inventory in a gaming situation



When the implicit shortage game phenomenon occurs, it makes the supplier overshoot large. The SGO model overshoots up to 7,335, bringing the average daily inventory from 1,954 to 2,722. Due to the opportunistic nature of buyers, suppliers must additionally acquire the ability to hold more than 4,000 inventories.

The reason for including outstanding orders in the shortfall game is that the reason for the shortage itself means that there is more demand than supply. Therefore, there can be no competition for price discounts, and since we are trying to secure inventory even by waiting, it makes real sense to reflect this. The cost of temporary inventory shortages was not taken into account. This is also because the shortage is a seller's market.

3) Shortfall games when you only know your competitor's information

We created a model in which one buyer knows how much another buyer orders and how much is allocated, and then determines the order quantity based on that information. This can yield the expected value of competitor information.

Buyer1 Prior Order Quantity=MAX(0, Buyer1 Target Inventory+Buyer1 Target Supply Line-Buyer1 Inventory-Buyer1 Supply Line+ Buyer1 Demand Forecasting)

Buyer1 Order Quantity=MIN(MAXOQ, MAX(Buyer1 Prior Order Quantity, XIDZ(Buyer1 Prior Order Quantity*B2OQ Forecasting, Supplier Inventory Forecasting-Buyer1 Prior Order Quantity

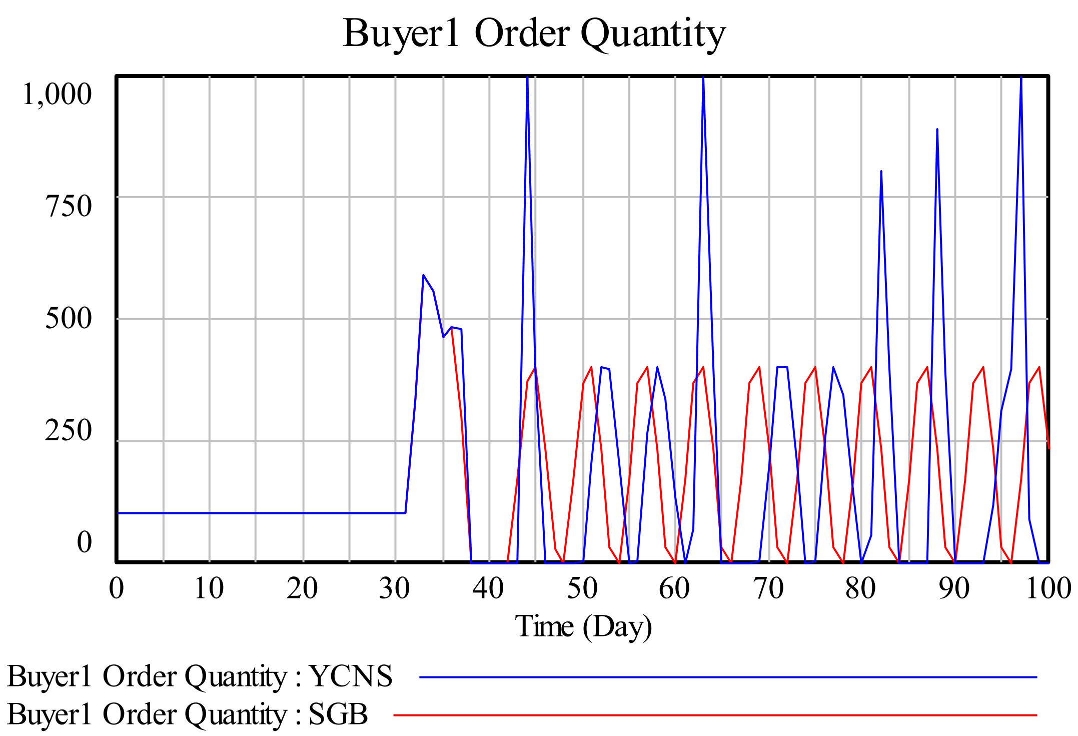
, Buyer1 Prior Order Quantity)))

Supplier Inventory Forecasting=SMOOTHI(Allocated Quantity for B1+Allocated Quantity for B2, Buyer Time, 200)

Buyer 1 can guess the supplier's inventory through the sum of the amount allocated by buyer 2 (Allocated Quantity for B2) and the amount allocated by Buyer 2 (Allocated Quantity for B1). Predict the sum of these two values (SMOOTHI, period = buyer time) and adjust the order amount.

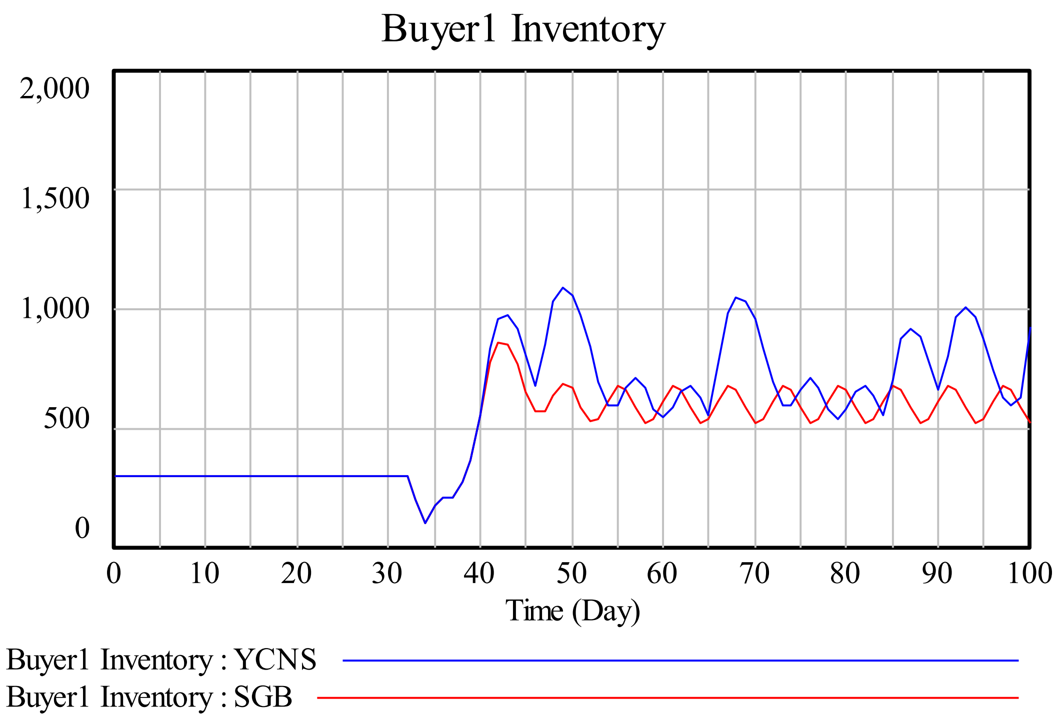
Buyer 2 also goes through the same process as Buyer 1. The simulation data file of the model created in this way was saved as YCNS.

<Figure 8-9> Shortfall game when there is competitor information but no supplier information



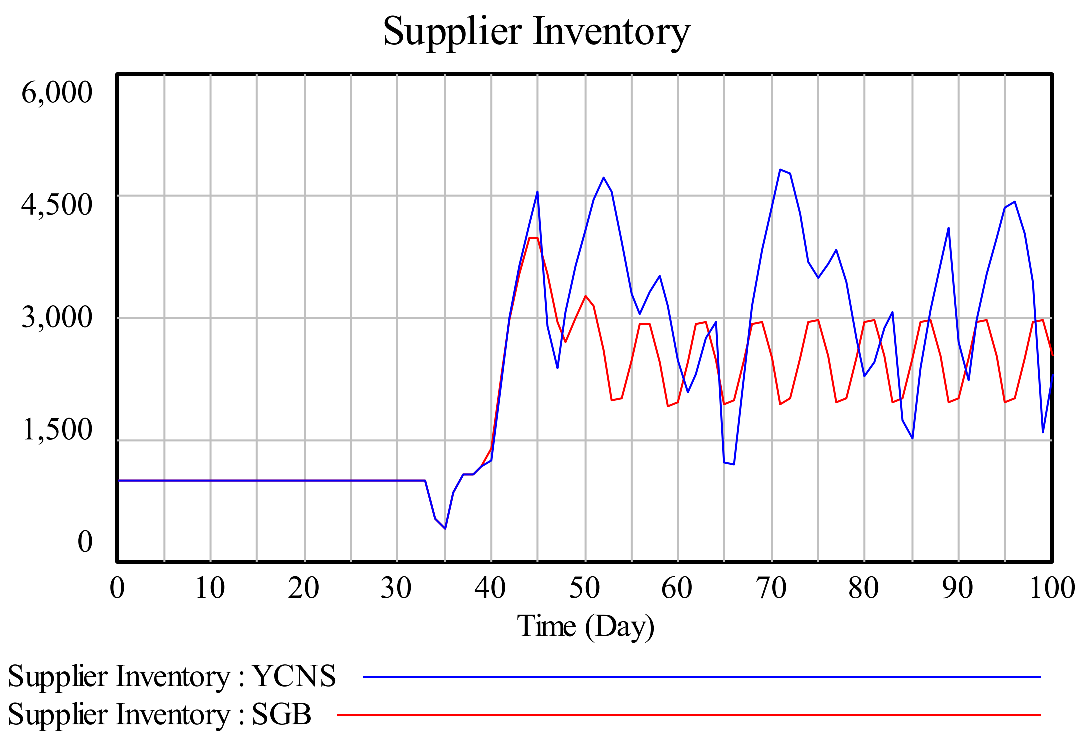
In the case of a model with only competitor information (YCNS), the order volume is usually amplified more often than the SGB (base model without a shortage game). Between 40 and 100 days, we can see an amplification of orders to 1,000 pieces. This is because they react very sensitively.

<Figure 8-10> Shortfall in the case of only competitor information (YCNS) Buyers1 Stock



While the base model has an average inventory of 484.80, the daily average of YCNS's Buyer 1 inventory is 574.06, a significant difference. It is judged to be due to the frequent overshoot.

<Figure 8-11> Supplier inventory in the shortfall game (YCNS) when you only have competitor information



In terms of supplier inventory, YCNS holds more than 10% of the inventory compared to the base model. If we limit the time to between 31 and 100 days, the difference is even greater.

Therefore, it has been shown that when we only have competitor information, the shortage game occurs due to inaccuracies in the information.

4) Analysis of external information effects

Even when you know information about your competitors or suppliers, shortage games can occur. 2) The game is a self-generated shortage game, and here it is a shortage game that occurs when the opponent exists, hence the name exogenous shortage game.

If Buyer1 knows how much Buyer2 has placed in the last 3 days (Buyer Time=3) and how much is in stock from the supplier, how much will he order? By predicting how much buyer 2 orders today (predicting using the Smooth function), buyer 1 will adjust the order volume, and likewise buyer 2 will adjust it, resulting in infinite repetition. Therefore, it is assumed here that we know the amount ordered yesterday. This can be done by using the Delay Fixed function in Vensim. For reference, the relation for Delay Buyer2 Order Quantity is as follows:

Delayed Buyer2 Order Quantity=DELAY FIXED(Buyer2 Order Quantity, 1, Buyer Demand)

where the Buyer Demand is 100. You must specify a value to enter on the first day (day 0).

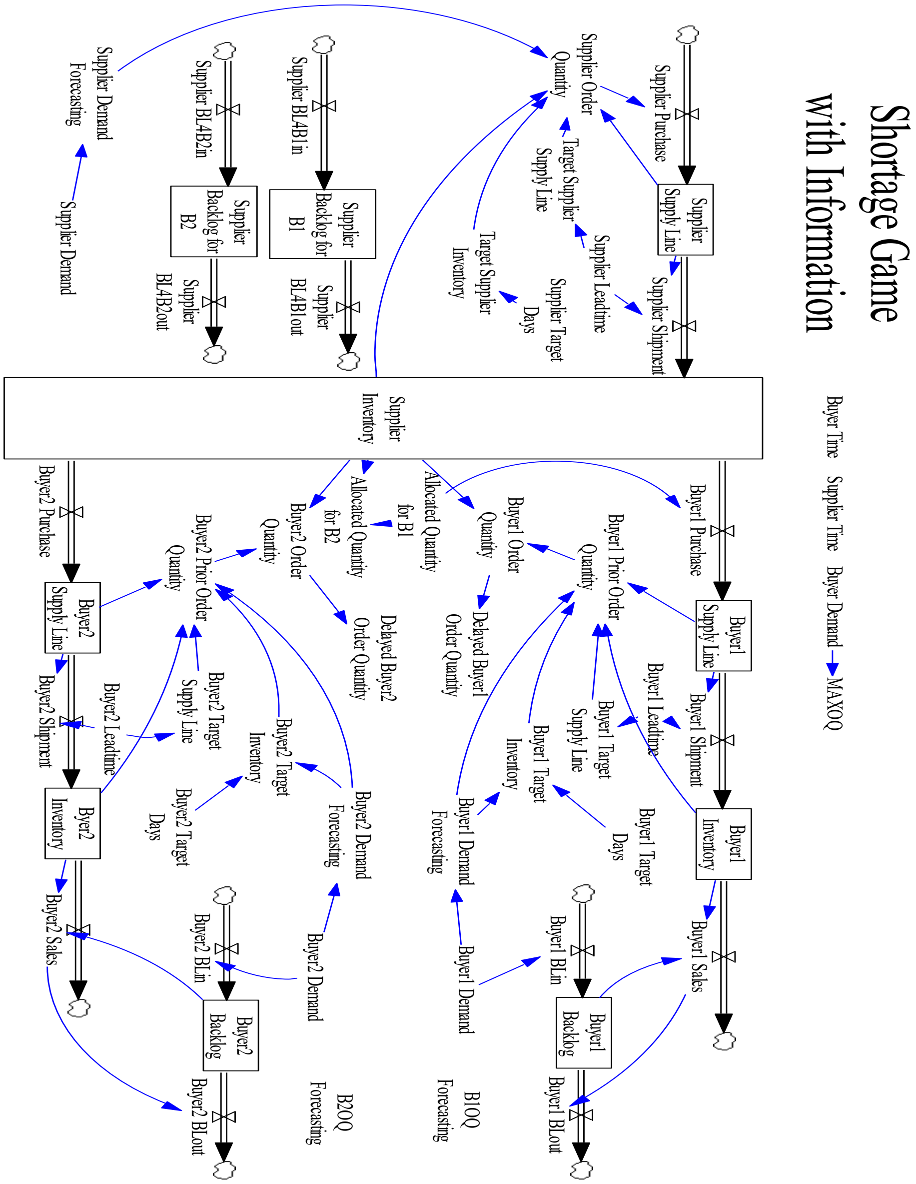
To find the required amount, it is simple to trace the calculation formula back to the proportional allocation of the supplier.

2) We used the relations discussed in section. Initially, the required order quantity is called Buyer Prior Order Quantity, and the actual order amount is called Buyer1 Order Quantity.

Buyer1 Order Quantity=MIN(MAXOQ, MAX(Buyer1 Prior Order Quantity, XIDZ(Buyer1 Prior Order Quantity*B2OQ Forecasting, Supplier Inventory-Buyer1 Prior Order Quantity, Buyer1 Prior Order Quantity)))

In the YCNS model, Supplier Inventory was predicted and used, but in the EXO model, Supplier Inventory information was modified so that it can be used immediately. In the relation of Buyer1 Order Quantity, replace Supplier Inventory Forecasting with Supplier Inventory.

<Figure 8-12> Shortfall game model when you know information about competitors' past orders and supplier inventory.



<Figure 8-9> contains more variables than <Figure 8-1> The relation is as follows:

Allocated Quantity for B1=MIN(Supplier Backlog for B1, Supplier Inventory*ZIDZ(Supplier Backlog for B1, Supplier Backlog for B1+Supplier Backlog for B2))

Allocated Quantity for B2=MIN(Supplier Inventory-Allocated Quantity for B1, MIN(Supplier Backlog for B2, Supplier Inventory*ZIDZ(Supplier Backlog for B2, Supplier Backlog for B1+Supplier Backlog for B2)))

B1OQ Forecasting=SMOOTHI(Delayed Buyer1 Order Quantity, Buyer Time, Buyer Demand)

B2OQ Forecasting=SMOOTHI(Delayed Buyer2 Order Quantity, Buyer Time, Buyer Demand)

Buyer Demand= 100

Buyer Time=3

Buyer1 Backlog= INTEG (Buyer1 BLin-Buyer1 BLout,Buyer Demand)

Buyer1 BLin=Buyer1 Demand

Buyer1 BLout=Buyer1 Sales

Buyer1 Demand Forecasting=SMOOTH(Buyer1 Demand, Buyer Time)

Buyer1 Demand=Buyer Demand+STEP(Buyer Demand, 31)

Buyer1 Inventory= INTEG (Buyer1 Shipment-Buyer1 Sales,Buyer1 Target Inventory)

Buyer1 Leadtime=Buyer Time

Buyer1 Order Quantity= MIN(MAXOQ, MAX(Buyer1 Prior Order Quantity, XIDZ(Buyer1 Prior Order Quantity*B2OQ Forecasting, Supplier Inventory-Buyer1 Prior Order Quantity, Buyer1 Prior Order Quantity)))

Buyer1 Prior Order Quantity=MAX(0, Buyer1 Target Inventory+Buyer1 Target Supply Line-Buyer1 Inventory-Buyer1 Supply Line+ Buyer1 Demand Forecasting)

Buyer1 Purchase=Allocated Quantity for B1

Buyer1 Sales=MIN(Buyer1 Inventory, Buyer1 Backlog)

Buyer1 Shipment=Buyer1 Supply Line/Buyer1 Leadtime

Buyer1 Supply Line= INTEG (Buyer1 Purchase-Buyer1 Shipment,Buyer1 Target Supply Line)

Buyer1 Target Days=Buyer Time

Buyer1 Target Inventory=Buyer1 Demand Forecasting*Buyer1 Target Days

Buyer1 Target Supply Line=Buyer1 Demand Forecasting*Buyer1 Leadtime

Buyer2 Backlog= INTEG (Buyer2 BLin-Buyer2 BLout,Buyer Demand)

Buyer2 BLin=Buyer2 Demand

Buyer2 BLout=Buyer2 Sales

Buyer2 Demand Forecasting=SMOOTH(Buyer2 Demand, Buyer Time)

Buyer2 Demand=Buyer Demand+STEP(Buyer Demand, 31)

Buyer2 Leadtime=Buyer Time

Buyer2 Order Quantity= MIN(MAXOQ, MAX(Buyer2 Prior Order Quantity, XIDZ(Buyer2 Prior Order Quantity*B1OQ Forecasting, Supplier Inventory-Buyer2 Prior Order Quantity, Buyer2 Prior Order Quantity)))

Buyer2 Prior Order Quantity=MAX(0, Buyer2 Demand Forecasting+ Buyer2 Target Supply Line+Buyer2 Target Inventory-Byer2 Inventory-Buyer2 Supply Line)

Buyer2 Purchase=Allocated Quantity for B2

Buyer2 Sales=MIN(Buyer2 Backlog, Byer2 Inventory)

Buyer2 Shipment=Buyer2 Supply Line/Buyer2 Leadtime

Buyer2 Supply Line= INTEG (Buyer2 Purchase-Buyer2 Shipment,Buyer2 Target Supply Line)

Buyer2 Target Days=Buyer Time

Buyer2 Target Inventory=Buyer2 Demand Forecasting*Buyer2 Target Days

Buyer2 Target Supply Line=Buyer2 Demand Forecasting*Buyer2 Leadtime

Byer2 Inventory= INTEG (Buyer2 Shipment-Buyer2 Sales,Buyer2 Target Inventory)

Delayed Buyer1 Order Quantity= DELAY FIXED (Buyer1 Order Quantity, 1, Buyer Demand)

Delayed Buyer2 Order Quantity=DELAY FIXED(Buyer2 Order Quantity, 1, Buyer Demand)

MAXOQ=Buyer Demand*10

Supplier Backlog for B1= INTEG (Supplier BL4B1in-Supplier BL4B1out,Buyer Demand)

Supplier Backlog for B2= INTEG (Supplier BL4B2in-Supplier BL4B2out,Buyer Demand)

Supplier BL4B1in=Buyer1 Order Quantity

Supplier BL4B1out=Buyer1 Purchase

Supplier BL4B2in=Buyer2 Order Quantity

Supplier BL4B2out=Buyer2 Purchase

Supplier Demand Forecasting=SMOOTHI(Supplier Demand, Supplier Time, 200)

Supplier Demand=Buyer1 Order Quantity+Buyer2 Order Quantity

Supplier Inventory= INTEG (Supplier Shipment-Buyer1 Purchase-Buyer2 Purchase,Target Supplier Inventory)

Supplier Leadtime=Supplier Time

Supplier Order Quantity=MAX(0, Target Supplier Inventory+Target Supplier Supply Line-Supplier Inventory-Supplier Supply Line+Supplier Demand Forecasting)

Supplier Purchase=Supplier Order Quantity

Supplier Shipment=Supplier Supply Line/Supplier Leadtime

Supplier Supply Line= INTEG (Supplier Purchase-Supplier Shipment,Target Supplier Supply Line)

Supplier Target Days=Supplier Time

Supplier Time=   5

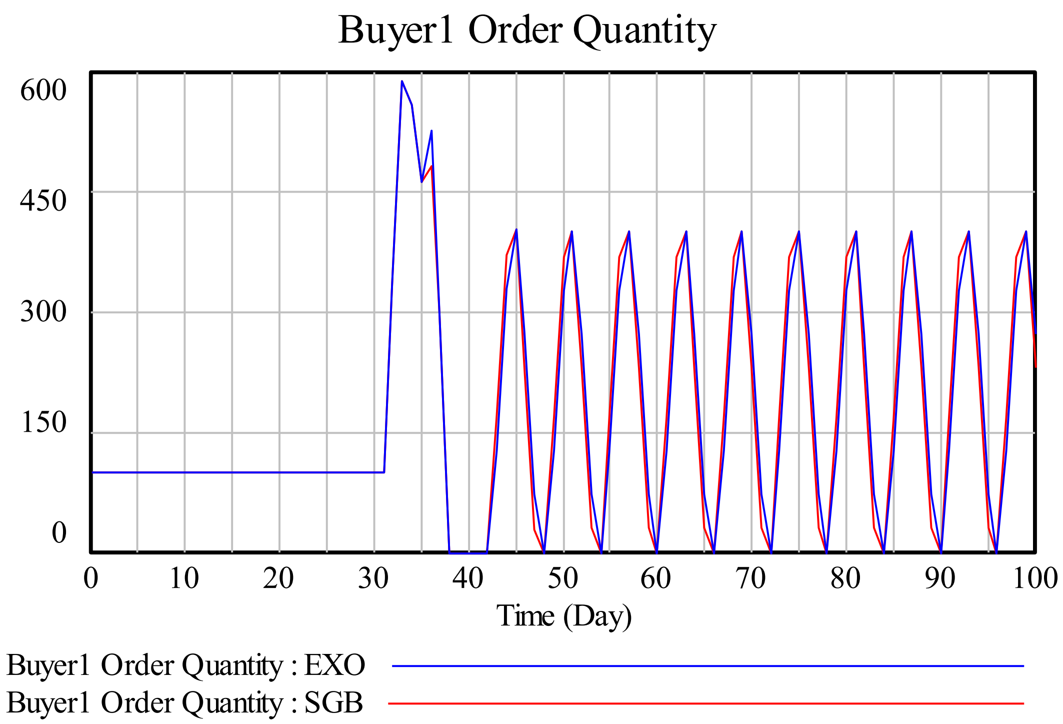
Target Supplier Inventory=Supplier Demand Forecasting*Supplier Target Days

Target Supplier Supply Line=Supplier Demand Forecasting*Supplier Leadtime

The simulation result of the exogenous shortage game model was expressed as EXO.

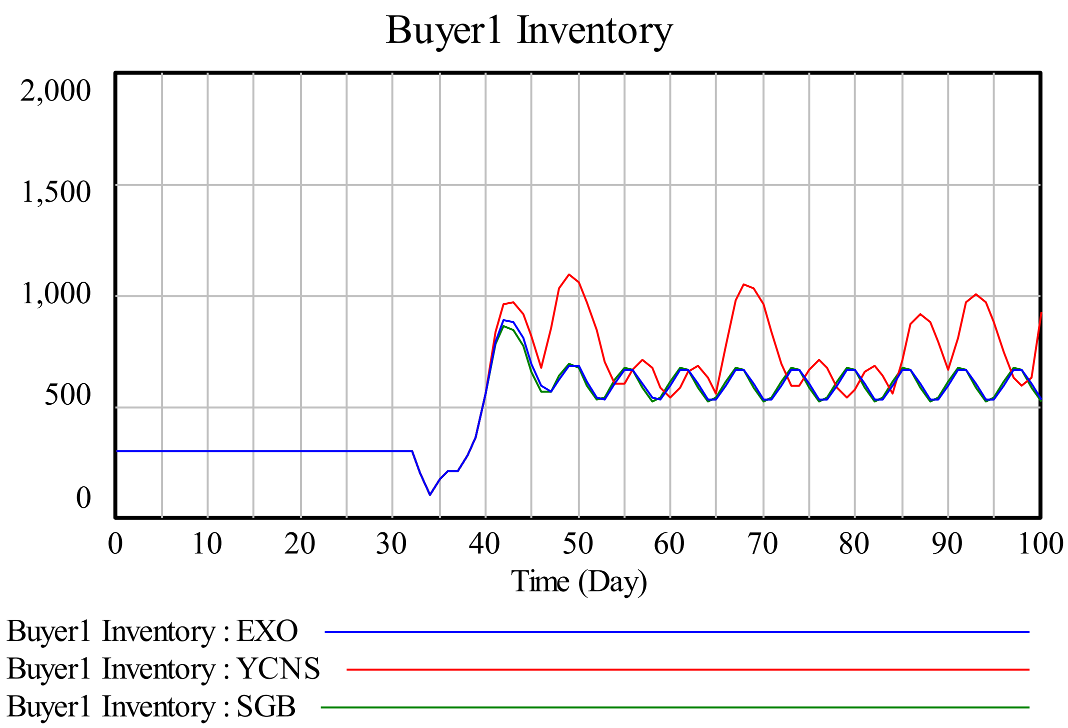
Looking at the inventory of buyer 1, the following <Figure 8-10> is shown.

<Figure 8-13> Buyer1's order volume in the EXO model



The order volume of the Buyer 1 of the EXO model is almost the same as that of the basic model (SGB). In other words, depending on the information effect, the phenomenon of the shortage game can almost be eliminated.

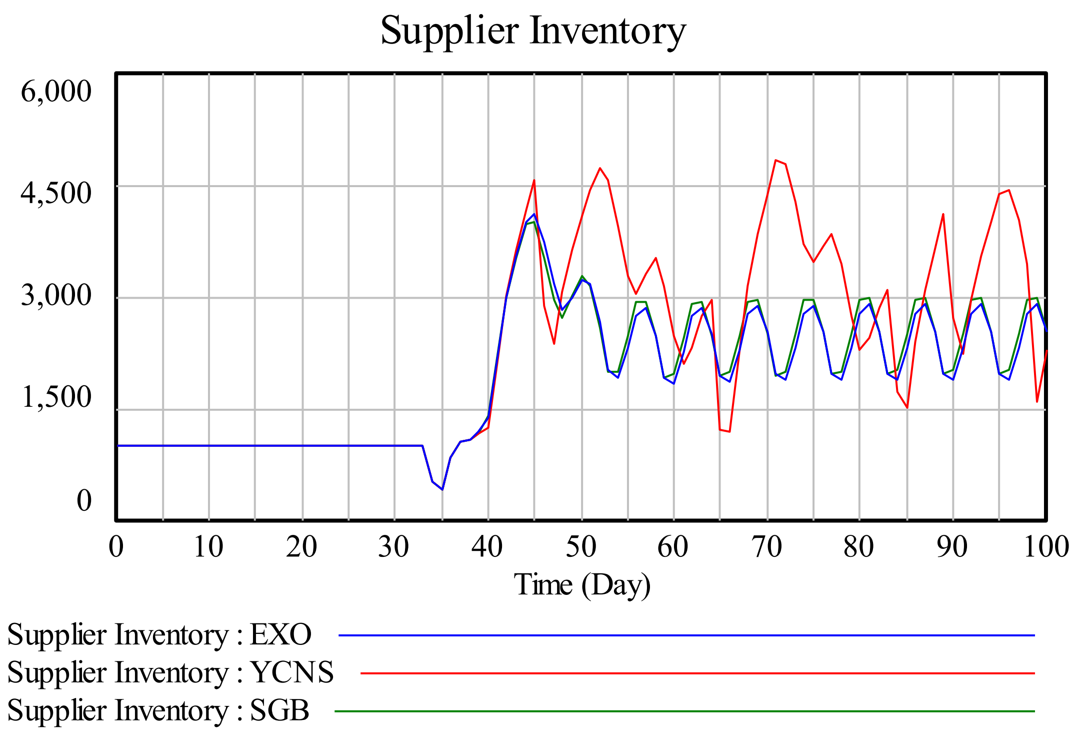
<Figure 8-14> Buyers of SGB, YCNS, and EXO models1 Inventory comparison



When comparing the three models, there is a much larger difference in having information about suppliers than when they have information only about competitors. The difference between EXO-YCNS is the difference in supplier information. For reference, EXO's Buyer 1's daily average of inventory is 486.69, YCNS is 574.06, and SGB is 484.80.

87 is the difference between receiving or guessing (YCNS-EXO=574-487=87) supplier inventory. Since you can't receive supplier information, you have to hold more than 10% of your inventory just by forecasting inventory. YCNS reproduced the situation under relatively complete information, and in this case, it was analyzed that it had a higher inventory than the model (SGB) that did not contain the mechanism of the shortage game, but the difference was not significant.

<Figure 8-15> Supplier Inventory Comparison of SGB, YCNS, and EXO Models

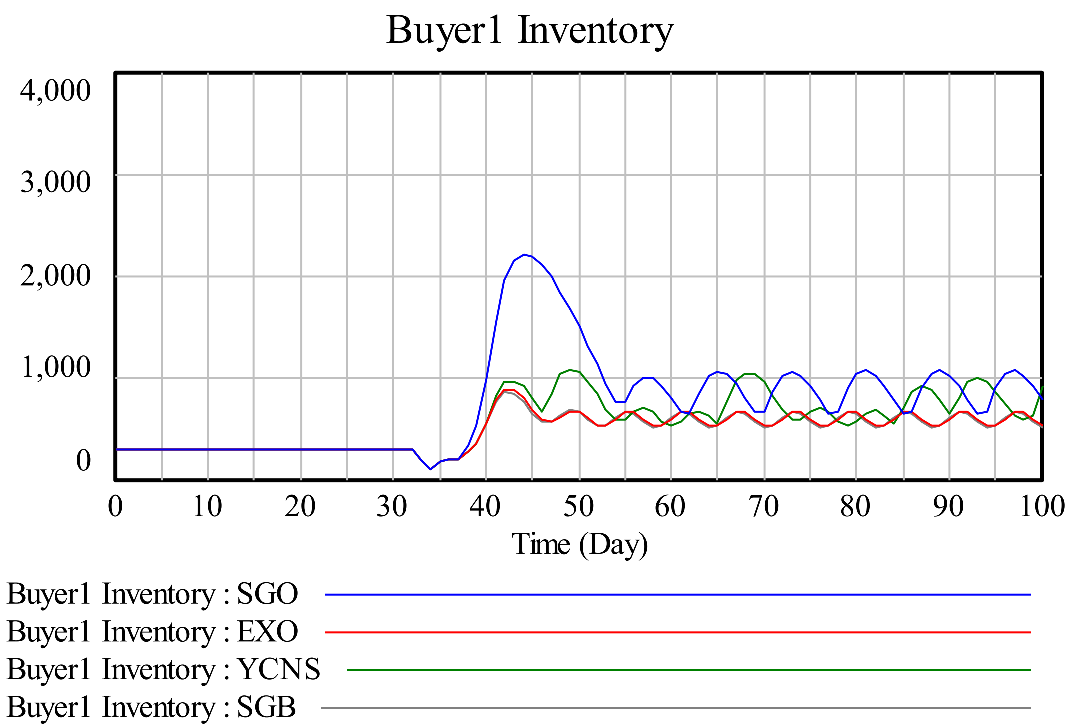


In terms of supplier inventory, it is similar to buyer inventory comparison. However, the absolute value of the difference is greater. Because it's upstream of the supply chain. The average supplier inventory for YCNS is 2,318 and for EXO it is 1,919. The difference is about 400. This difference is significantly larger than the difference 87 in buyer 1. Small differences in buyers are amplified as they move upstream in the supply chain. When optimizing the entire supply chain, suppliers' share of inventory can play a larger role.

From the above analysis, several points can be inferred:

First, there are a variety of factors that cause the shortage game, of which intrinsic factors play a greater role than extrinsic factors.

<Figure 8-16> Buyers in four models1 Stock



As shown in <Figures 8-16> the blue color is SGO, which is a shortfall game of inherent factors. It is a model that uses a moving average of 3 periods to compare the amount ordered with the amount allocated to increase or decrease the amount of one's order.

Second, in information effects, both information about competitors and information about suppliers are affected. However, information about the provider can have a greater impact. YCNS was a model that guessed because there was competitor information but no supplier information, and the EXO model was a model that knew supplier information. Information upstream of the supply chain was analyzed as more valuable than information about competitors.

Third, it was analyzed that the information value is very high. With information about competitors and buyers, it shows that even if the buyer adjusts the order volume, the shortfall game does not occur much. It suggests that making informed decisions can reduce amplification.

Chapter 9

Transport capacity optimization

Transportation Capacity Optimization

1) Transportation differentiation

The highest proportion of logistics costs is transportation costs. Therefore, it is necessary to make efforts to increase customer satisfaction with fewer vehicles. To solve the following problems, create a simulation model and find the optimal value.

OO engine performs the function of distributing trucks. Demand for trucks is about 100 per hour . But there is a hierarchy of customers. Customer A accounts for 20% of the demand. However, it is a very important customer for O O institutions, so it must be dispatched first. Group B accounts for 30% of the demand. Importance is lower than A and higher than C. Group C accounts for 50% of the demand, but the importance is low. As a result of past analysis, group A is judged to be between 10-20 in importance, B is judged to be between 5-15, and group C is judged to be between 0 and 10. This importance is relative, not absolute.

Transit times are daily and take from 2 to 6 hours. With an average of 4 hours, the OO agency operates a total of 400 units.

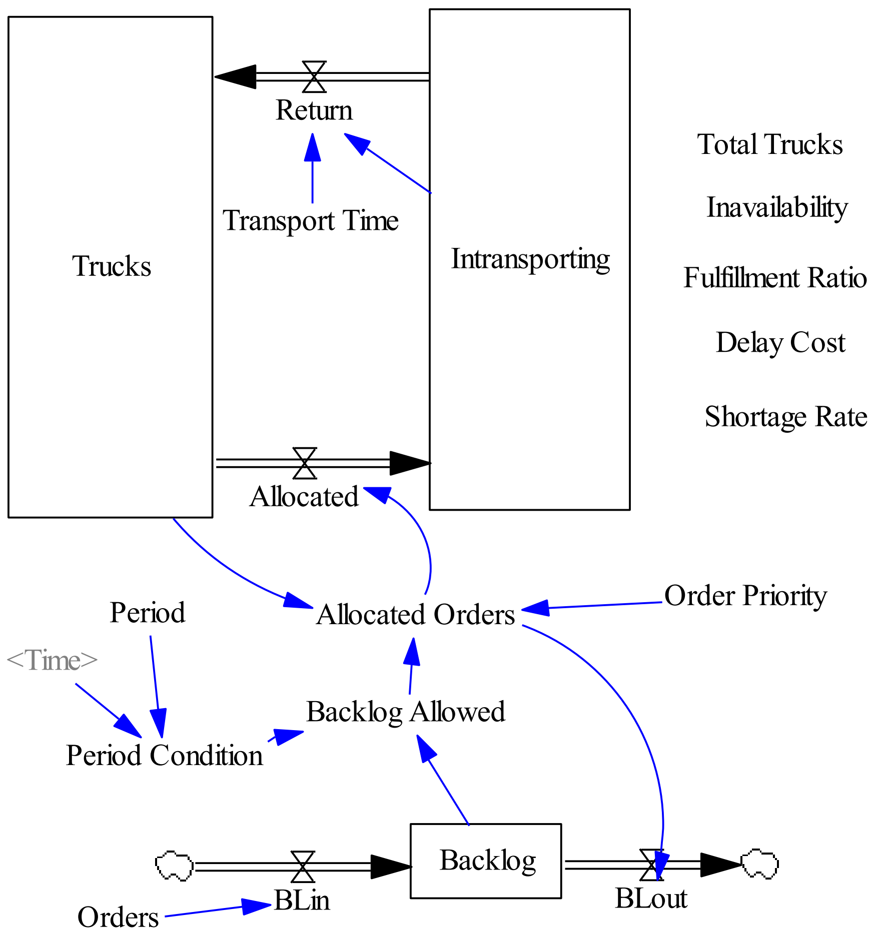
Table 9-1< > Demand and Importance by Customer Group

	demand	Importance
A	N ormal(20, 10)	15(10-20)
B	Normal(30,15)	10(5-15)
C	Normal(50, 25)	5(0-10)

The OO agency believes that the total number of trucks is insufficient. The process of increasing the number of trucks is complicated, so for now, we want to increase the A fulfillment rate.

To solve this problem, we created the following model:

<Figure 9-1> Customer-Specific Transport Truck Allocation Model



The relations used in this model are as follows:

Allocated Orders[DDD]=ALLOCATE BY PRIORITY(Backlog Allowed[DDD], Order Priority[DDD], 3, 10, Trucks)

Allocated=SUM(Allocated Orders[DDD!])

Backlog Allowed[DDD]=Backlog[DDD]*Period Condition

Backlog[DDD]= INTEG (BLin[DDD]-BLout[DDD],20)

BLin[DDD]=Orders[DDD]

BLout[DDD]=Allocated Orders[DDD]

DDD:A, B, C

Delay Cost[DDD]=Shortage Rate[DDD]*Order Priority[DDD]

Fulfillment Ratio[DDD]=XIDZ(Allocated Orders[DDD], Backlog[DDD], 1)*Period Condition*Period

Inavailability=Trucks/Total Trucks

Intransporting= INTEG (Allocated-Return,0)

Order Priority[DDD]=15,10,5

Orders[A]=RANDOM NORMAL(0, 40, 20, 10, 1234) ~~|

Orders[B]=RANDOM NORMAL(0, 60, 30, 15, 3456) ~~|

Orders[C]=RANDOM NORMAL(0, 100, 50, 25, 5678)

Period Condition=IF THEN ELSE(MODULO(Time, Period)=0, 1, 0)

Period=1

Return= Intransporting/Transport Time

Shortage Rate[DDD]=MAX(0, Backlog[DDD]-Allocated Orders[DDD])

Total Trucks=400

Transport Time=RANDOM UNIFORM(2, 6, 4567)

Trucks= INTEG (Return-Allocated,Total Trucks)

The simulation was run with some parameter changes. We implemented a method of allocating without differentiating for the three demands. In this case, Order Priority = 10,10,10. 1,1,1 is acceptable. You just need to apply the same attractiveness. If it is allocated equally every hour, the data file name is N1h. In the method of allocating by the Allocation by Priority module, if it is allocated every 3 hours with different attractiveness, it is called P3h.

2) Effects of prioritization

Compare N1h with P1h. It refers to the case of equal allocation every hour and the case of priority allocation every hour. When executed on random numbers, the average number of Group A orders (Orders) was 21, Group B orders were 26.64, and Group C orders were 49.31. It was intended to occur in a relative ratio of 2:3:5, but the results were very small for group B. This is an analysis of only 80 hours between 21 and 100 hours out of the total period in which the simulation was performed.

<Table 9-2> Table 9 Comparison by Customer Group for Allocated Trucks for N1h and P1h

	A	B	C
Ph1	21.29	26.26	35.97
Nh1	18.59	22.60	42.34

For A and B, a higher amount was allocated when priority was assigned than when equal allocation was made. C, on the other hand, was assigned more equal allocations.

<Table 9-3> Comparison of N1h and P1h Fulfillment Ratios by Customer Group

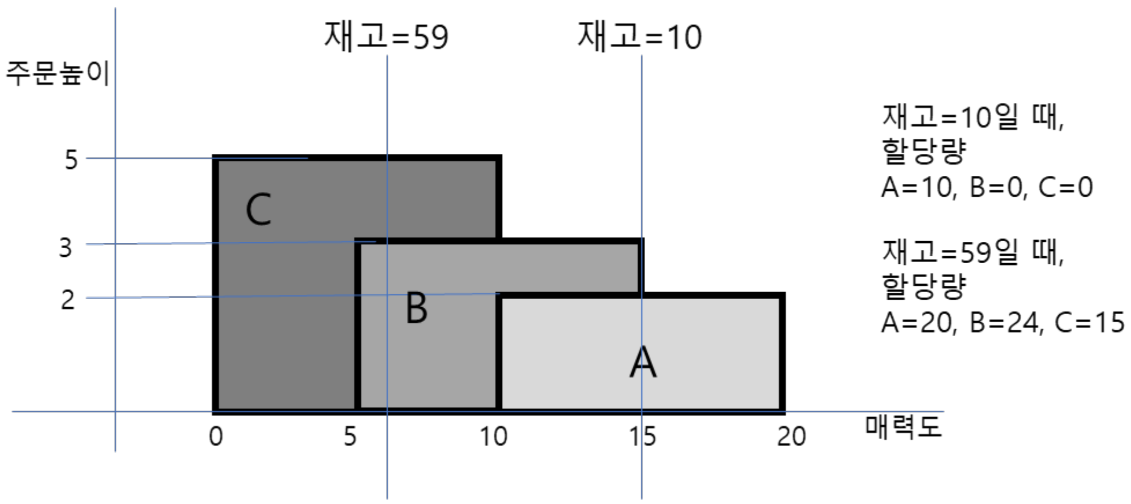
	A	B	C
Ph1	0.9970	0.5671	0.0709
Nh1	0.1385	0.1385	0.1385

The low demand fulfillment rate is due to trucks allocated to backlog (unpaid) minutes. If a white rock is not assigned on a specific day, it remains and awaits reassignment the next day. In the case of C orders, because they are not allocated continuously, the backlock value continues to increase, resulting in a very poor fulfillment rate. The value in Table 9-2> < is calculated even if it is assigned due to delay, so it does not reflect the delay (service part) characteristic. Since the simulation is run on an hourly basis, it means that 99.7% of customer orders allocated within one hour are allocated in A.

When prioritization occurs when supply is scarcer than demand, i.e., when allocations must be made, A has a fulfillment rate of nearly 100%, while C has a very low fulfillment rate.

The allocation mechanism of Allocation by priority follows the Wood Algorithm. This can be illustrated by the following figure.

<Figure 9-2> Allocation mechanism of the Wood algorithm



The order quantity of A is 20 pieces, and the attractiveness is between 10 and 20. B has an order quantity of 30 pieces and an attractiveness of 5 to 10. C has a quantity of 50 orders and an attractiveness between 0 and 10. The order quantity can be placed in a square based on attractiveness. The area of the rectangle becomes the quantity of each order. Attractiveness is given in Priority. In Allocation by Priority, enter 10 for width. When you have 10 inventories and the total sum of orders is 100, all 10 are assigned to A because priority assignment follows a mechanism of filling one by one from the right side of the figure. If there are 59 stocks, A is allocated 20, B is allocated 24, and C is assigned 15. Of course, if there are 1 00 pieces in stock, each order will be allocated without any shortage.

In comparison, equal allocation is equivalent to Proportional allocation. You will receive it according to the proportion of the order volume. With proportional allocation, if the orderer knows the supplier's proportional allocation rules, a shortfall game can occur depending on the opportunistic nature. This does not reflect on the shortfall game.

3) Effects on the allocation cycle

If demand is divided into A, B, and C according to importance, the truck allocation will try to increase the service rate for A. It is possible to allocate all trucks to C at a certain point in time and not be able to allocate them according to order A at the next time. Therefore, the allocator thinks it would be good to collect and manage the demand a little more. In other words, instead of allocating demand generated for 1 hour, I think that if we collect demand for 2 hours and allocate it all at once, the satisfaction rate for A will be higher. To see the effect of this, run the simulation by increasing the allocation period to 2 hours, 3 hours, and 4 hours to the model > <Figure 9-1.

Table 9-4> < Fulfillment Ratio by Assignment Cycle

	A	B	C
P1h	0.997	0.5671	0.0709
P2h	1	0.5731	0.0731
P3h	1.012	0.5734	0.0675
P4h	1	0.5466	0.0466

A There is little change in the fulfillment rate for demand. A value higher than 1 is calculated by limiting the time setting to 21 to 100 hours. In addition, it may also be caused by rounding. There is a slight change in demand but only marginally. It is best to do it in a group of 3 hours, and if you go to 4 hours, it drops by a rather large margin. C demand is greatest at 2 hours and smallest at 4 hours.

Let's take a look at how trucks can be utilized better for providers who supply trucks. In <Figure 9-1>, the amount in the stock variable called trucks is the queue waiting to be serviced. From the truck provider's point of view, it was named Availability, as it indicates the availability of the truck. The Intransportation on the right shows the number of trucks being transported . The percentage of trucks in total trucks (Total Trucks = 400) refers to the ability to provide service, but because it is the amount in waiting, it is an unused resource. The higher the value of the trucks, the worse it is.

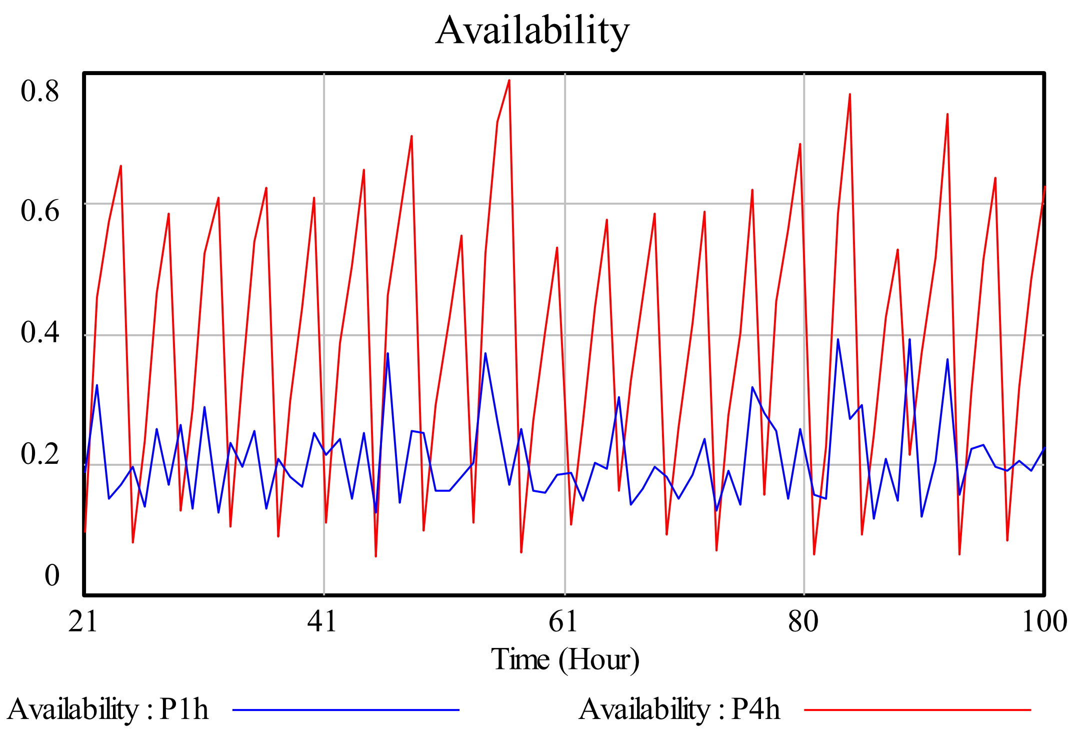
Table 9-4< > Truck availability by allocation cycle (Availability=Trucks/Total Trucks)

	Idle Rate
P1h	0.2088
P2h	0.2731
P3h	0.3380
P4h	0.3913

The larger the allocation cycle, the higher the availability. Even though trucks are on standby, tying orders to better serve high-priority demand has been shown to lead to inefficiencies.

For reference, the following <Figure 9-3> shows the availability of P 1h and P4h.

<Figure 9-3> Availability of P1h and P4h



In the case of the blue line located below, it goes out and enters every hour, so the idle rate is formed below 0.4. On the other hand, the red line P4h drops close to zero in times of 4 for the truck to leave (it actually drops to zero, and then there is an incoming value, which is greater than zero), but it reaches its peak in the time before the truck is allocated. Transit times are volatile, so there are deviations. Idle trucks can reach as high as 0.8. This means that about 300 out of 400 are resting.

4) Truck-allocation system on a daily basis

By setting Time Step=0.5 days and modifying some parameters in the model such as <Figure 9-1> you can create a daily truck allocation system.

Allocated Orders[DDD]=ALLOCATE BY PRIORITY(Backlog Allowed[DDD], Order Priority[DDD], 3, 10, Trucks)

Allocated=SUM(Allocated Orders[DDD!])

Availability=Trucks/Total Trucks

Backlog Allowed[DDD]=Backlog[DDD]*Period Condition

Backlog[DDD]= INTEG (BLin[DDD]-BLout[DDD],20)

BLin[DDD]=Orders[DDD]

BLout[DDD]=Allocated Orders[DDD]

DDD:A, B, C

Delay Cost[DDD]=Shortage Rate[DDD]*Order Priority[DDD]

Fulfillment Ratio[DDD]=XIDZ(Allocated Orders[DDD], Backlog[DDD], 1)*Period Condition*Period

Intransporting= INTEG (Allocated-Return,0)

Order Priority[DDD]=15,10,5

Orders[A]=IF THEN ELSE(MODULO(Time, 1)=0, RANDOM NORMAL(0, 40, 20, 10, 1234), 0) ~~|

Orders[B]=IF THEN ELSE(MODULO(Time, 1)=0, RANDOM NORMAL(0, 60, 30, 15, 3456), 0) ~~|

Orders[C]=IF THEN ELSE(MODULO(Time, 1)=0, RANDOM NORMAL(0, 100, 50, 25, 5678), 0)

Period Condition=IF THEN ELSE(MODULO(Time, Period)=0, 1, 0)

Period= 1

Return= Intransporting/Transport Time

Shortage Rate[DDD]=MAX(0, Backlog[DDD]-Allocated Orders[DDD])

Total Trucks=100

Transport Time=0.5

Trucks= INTEG (Return-Allocated,Total Trucks)

It is a system that collects orders for one day and delivers them the next day. Compare it with a system that increases the one-day transport order to two days and delivers it the next day. D1 is when you collect orders once a day, and D2 is a system that collects and allocates demand for two days.

Table 9-6> < Fulfillment Ratio for daily assignments and once every two days

	A	B	C
D2	0.5023	0.2690	0.0290
D1	0.5024	0.5	0.4085

If it is bundled for two days, A is preserved, but the satisfaction rate of B and C drops sharply. Of course, because of the use of backrock, it must be taken into account that the customer satisfaction rate is underestimated. Even considering this, it can be seen that the fulfillment rate of C is very low.

The availability of D 2, i.e. the probability that trucks will remain in trucks, is very high in D2. It can be seen that the availability of trucks is very low. This needs to be analyzed later. The availability of D1 was 0.8766, while the availability of D2 decreased considerably to an average of 0.7646 per day. Since it is delivered once every two days, the truck is underutilized.

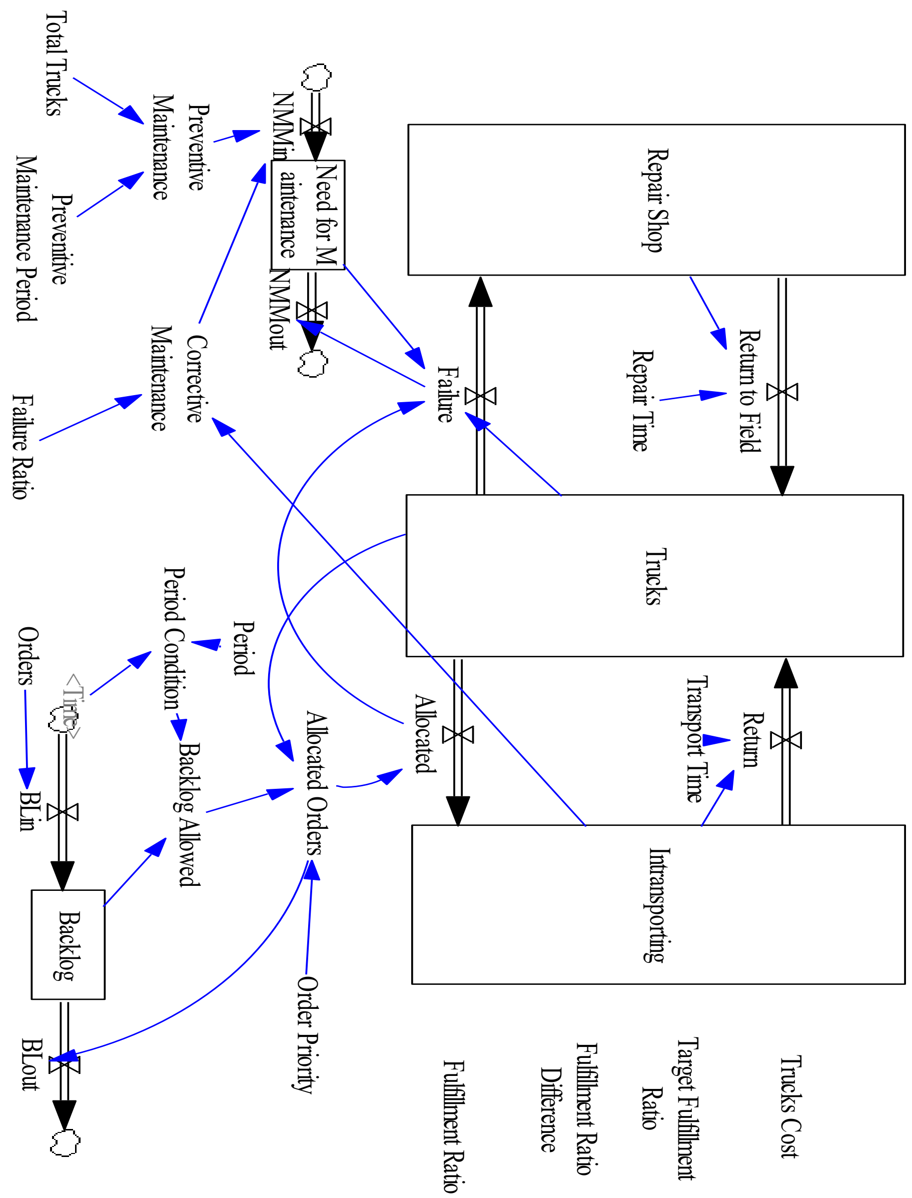
A system that starts from zero base every day fits the typical newsvendor model.

5) Service capability estimation

Earlier, we focused on how to allocate capacity (trucks) by demand in preparation for truck demand. The model used earlier was extended to create a model for determining the number of trucks. Trucks enter the workshop due to preventive maintenance and breakdown maintenance. To calculate overall capabilities, key variables must be included. There may be other important variables, but only maintenance has been considered here.

The model considering the maintenance element is shown in the following <Figure 10-1>.

<Figure 9-4> Truck counting model including maintenance



Allocated Orders[DDD]= ALLOCATE BY PRIORITY(Backlog Allowed[DDD], Order Priority[DDD], 3, 10, Trucks)

Allocated=SUM(Allocated Orders[DDD!])

Backlog Allowed[DDD]= Backlog[DDD]*Period Condition

Backlog[DDD]= INTEG (BLin[DDD]-BLout[DDD],20)

BLin[DDD]=Orders[DDD]

BLout[DDD]=Allocated Orders[DDD]

Corrective Maintenance=Intransporting*Failure Ratio

DDD:A, B, C

Failure Ratio=0.01

Failure= MIN(Trucks-Allocated, Need for Maintenance)

Fulfillment Ratio Difference=Target Fulfillment Ratio-SUM(Fulfillment Ratio[DDD!]) /3

Fulfillment Ratio[DDD]=Allocated Orders[DDD]/Backlog[DDD]

Intransporting= INTEG (Allocated-Return,0)

Need for Maintenance= INTEG (NMMin-NMMout,0)

NMMin=   Corrective Maintenance+Preventive Maintenance

NMMout=Failure

Order Priority[DDD]=15,10,5

Orders[A]=RANDOM NORMAL(0, 40, 20, 10, 1234) ~~|

Orders[B]=RANDOM NORMAL(0, 60, 30, 15, 3456) ~~|

Orders[C]=RANDOM NORMAL(0, 100, 50, 25, 5678)

Period Condition=IF THEN ELSE(MODULO(Time, Period)=0, 1, 0)

Period= 1

Prevenitive Maintenance Period=1440

Preventive Maintenance=Total Trucks/Prevenitive Maintenance Period

Repair Shop= INTEG (Failure-Return to Field,0)

Repair Time=168

Return to Field=Repair Shop/Repair Time

Return= Intransporting/Transport Time

Target Fulfillment Ratio=0.9

Total Trucks=400

Transport Time=RANDOM UNIFORM(2, 6, 4567)

Trucks Cost=Total Trucks*1

Trucks= INTEG (Return+Return to Field-Failure-Allocated,Total Trucks)

FINAL TIME = 10000 Hour

INITIAL TIME = 0 Hour

TIME STEP = 1 Hour

The truck was supposed to undergo preventive maintenance once every 1,440 hours. It is assumed that it operates for 8 hours a day and performs preventive maintenance once every 6 months.

Breakdown maintenance was modeled as a breakdown occurring while in operation, and then heading to the workshop after the truck came in. It was assumed that a failure would occur with a probability of 0.001 in 1 hour.

All maintenance was set to take 40 hours. Based on the 8-hour standard, it was assumed that it would take about 5 days.

Everything headed to the workshop, including preventive maintenance and breakdown maintenance, was named Failure.

In order to aim for a satisfaction rate of 90% of the total demand, minimize the need for maintenance, and take as few trucks as possible, the optimization objective function (Payoff function) was set as follows.

Fulfillment Ratio Difference/-5

Trucks Cost/-0.01

Need for Maintenance/-0.001

When optimized, the total number of trucks required was 674.742.

Compare the variables between 400 and 674.742 trucks.

First , if we look at the target customer satisfaction rate,

Table 9-7 < > Fulfillment Ratio Comparison

	A	B	C	T otal
1h400	0.9923	0.4945	0.0026	0.34811
TO1h	1	0.9726	0.8401	0.91183

Different values appear depending on the weight in the objective function of the optimization. Here, as suggested above, we weighted -5 for Fulfillment Ratio Difference, -0.01 for Truck Cost, and -0.001 for Need for Maintenance. You may have questions about how to weight them. Enter a comparison between the actual costs incurred or an estimate of the utility at the target value. Depending on what to optimize, the weight of the objective function should be different.

As a result, with about 675 units, the overall customer satisfaction rate exceeds 90%. For those in the 400s, it was only 35 percent. In other words, if you aim to meet the target by more than 90%, you will need about 675 trucks.

Of the total 674.74 trucks, 164.38 (24%) remained in the repair shop over the entire period, while the average number of trucks in transit was 365.89 (54%). The average number of trucks waiting to load goods is 144.46 (21%: 99% of the total, which is a rounding problem.) is the zone.

1Chapter 0

Effects of using emergency channels

An Emergency Channel in the Supply Chain

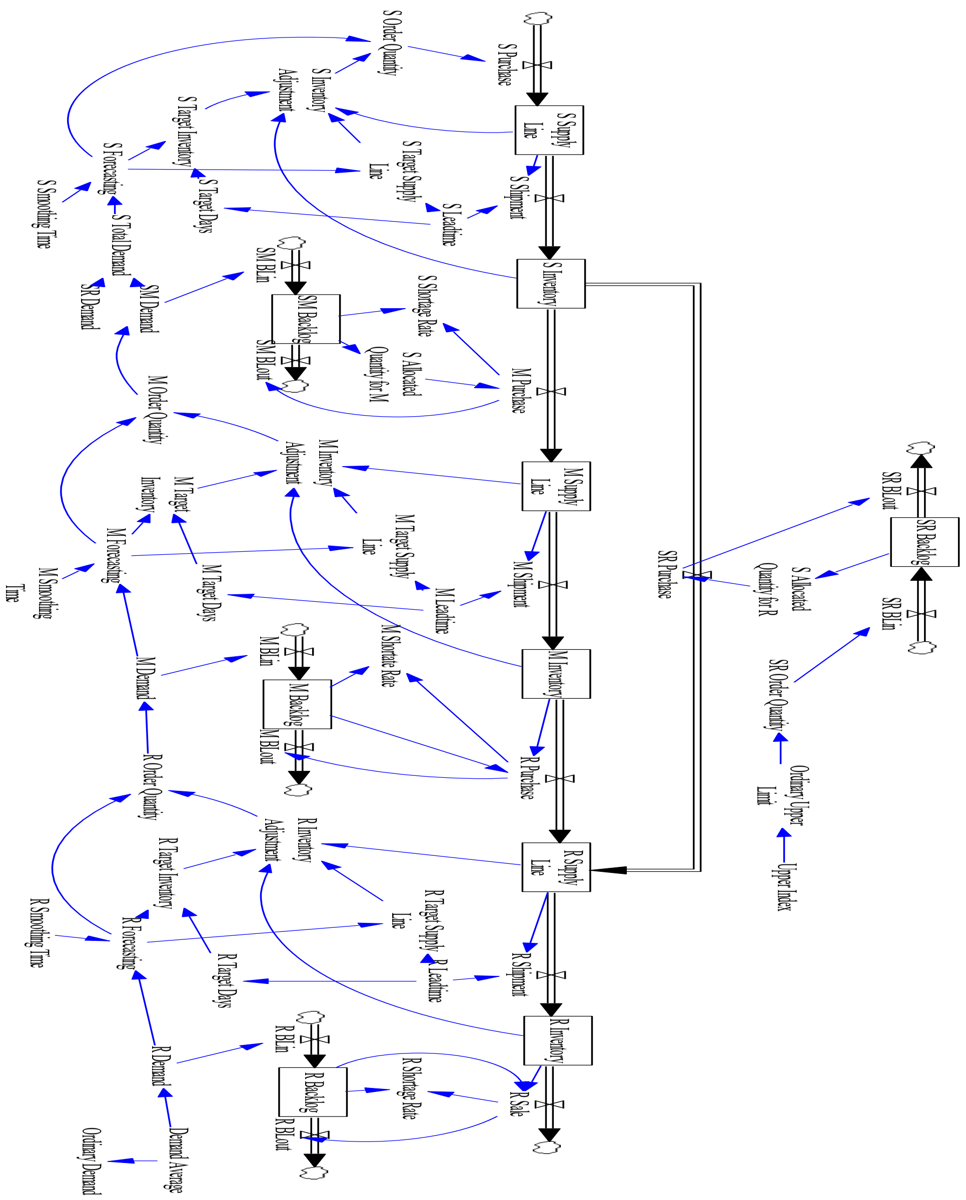
In the three-stage supply chain of S-M-R, which we have mainly covered so far, we will examine the effect of the supply chain in which R directly orders and dictates to S for more than a certain amount of demand. The supply chain that contrasts is, of course, the three-stage supply chain of SMR.

In the three-stage supply chain of SMR, S is in a rhythm of forecasting, leading, and adjusting in 7-day increments, M is in 5-day increments, and R is in 3-day rhythms. When R is in a hurry with S, the channel that can get help is called the emergency channel.

In the case of having an emergency channel, it can be expected that the stability of M located in the middle increases. Since it only responds to a certain range of R demands, M's inventory level will be lower. If M stabilizes in demand and order volume, it is likely that S accepting it will also stabilize. However, depending on how large the cost of direct delivery to R, which is an additional burden that S obtains, determines whether to place an emergency channel. However, if the demand for R has a pulse function and the pulse duration is only 10 days, the additional burden of S will not be significant.

To measure the quantitative effect of emergency channels, we compare a basic three-stage supply chain that responds to the same R demand with a supply chain with an emergency channel as shown in the following <Figure 10-1> Hereinafter, the basic supply chain is called the B model, and the model with an emergency channel is called the E model. Model B is omitted here because it has been repeatedly presented earlier. Just recall the model called 357 above. However, the demand for R has changed to 100+100*Pulse(31, 10). This R demand is 100 from the beginning to the 30th, and then represents the demand of 200 from the 31st to the 40th. From the 41st, it goes back to 100 and shows 100 until the last 100.

<Figure 10-1> Three-stage supply chain model with emergency channels



The relations used in the E model are as follows.

Demand Average=100

M Backlog= INTEG (M BLin-M BLout,100)

M BLin=M Demand

M BLout=R Purchase

M Demand=MAX(0, R Order Quantity-SR Order Quantity)

M Forecasting= SMOOTH(M Demand, M Smoothing Time)

M Inventory Adjustment=M Target Supply Line-M Supply Line+M Target Inventory-M Inventory

M Inventory= INTEG (M Shipment-R Purchase,M Target Inventory)

M Leadtime=5

M Order Quantity=MAX(0, M Forecasting+M Inventory Adjustment)

M Purchase=S Allocated Quantity for M

M Shipment=M Supply Line/M Leadtime

M Shortate Rate=MAX(0, M Backlog-R Purchase)

M Smoothing Time=5

M Supply Line= INTEG (M Purchase-M Shipment,M Target Supply Line)

M Target Days= M Leadtime

M Target Inventory=M Forecasting*M Target Days

M Target Supply Line=M Forecasting* M Leadtime

Ordinary Demand=Demand Average*1.2

Ordinary Upper Limit=Demand Average*Upper Index

R Backlog= INTEG (R BLin-R BLout,100)

R BLin= R Demand

R BLout=R Sale

R Demand=Demand Average+Demand Average*PULSE(31, 10)

R Forecasting=SMOOTH(R Demand, R Smoothing Time)

R Inventory Adjustment=R Target Inventory-R Inventory+R Target Supply Line-R Supply Line

R Inventory= INTEG (R Shipment-R Sale,R Target Inventory)

R Leadtime=3

R Order Quantity=MAX(0, R Forecasting+R Inventory Adjustment)

R Purchase=MIN(M Inventory, M Backlog)

R Sale=MIN(R Backlog, R Inventory)

R Shipment=R Supply Line/R Leadtime

R Shortage Rate=MAX(0, R Backlog-R Sale)

R Smoothing Time=3

R Supply Line= INTEG (R Purchase-R Shipment+SR Purchase,R Target Supply Line)

R Target Days= R Leadtime

R Target Inventory=R Forecasting*R Target Days

R Target Supply Line=R Forecasting*R Leadtime

S Allocated Quantity for M=MIN(SM Backlog, S Inventory*XIDZ(SM Backlog, SM Backlog+SR Backlog, 0))

S Allocated Quantity for R=MIN(SR Backlog, S Inventory*XIDZ(SR Backlog, SM Backlog+SR Backlog, 0))

S Forecasting=SMOOTH(S Total Demand, S Smoothing Time)

S Inventory Adjustment=S Target Inventory-S Inventory+S Target Supply Line-S Supply Line

S Inventory= INTEG (S Shipment-M Purchase-SR Purchase,S Target Inventory)

S Leadtime=7

S Order Quantity=MAX(0, S Inventory Adjustment+S Forecasting)

S Purchase=S Order Quantity

S Shipment=S Supply Line/S Leadtime

S Shortage Rate=MAX(0, SM Backlog-M Purchase)

S Smoothing Time=7

S Supply Line= INTEG (S Purchase-S Shipment,S Target Supply Line)

S Target Days=S Leadtime

S Target Inventory=S Forecasting*S Target Days

S Target Supply Line=S Forecasting*S Leadtime

S Total Demand=SM Demand+SR Demand

SM Backlog= INTEG (SM BLin-SM BLout,100)

SM BLin=SM Demand

SM BLout=M Purchase

SM Demand=M Order Quantity

SR Backlog= INTEG (SR BLin-SR BLout, 0)

SR BLin=SR Order Quantity

SR BLout=SR Purchase

SR Demand=SR Order Quantity

SR Order Quantity=IF THEN ELSE(R Order Quantity>=Ordinary Upper Limit, R Order Quantity-Ordinary Demand, 0)

SR Purchase=S Allocated Quantity for R

Upper Index=1.2

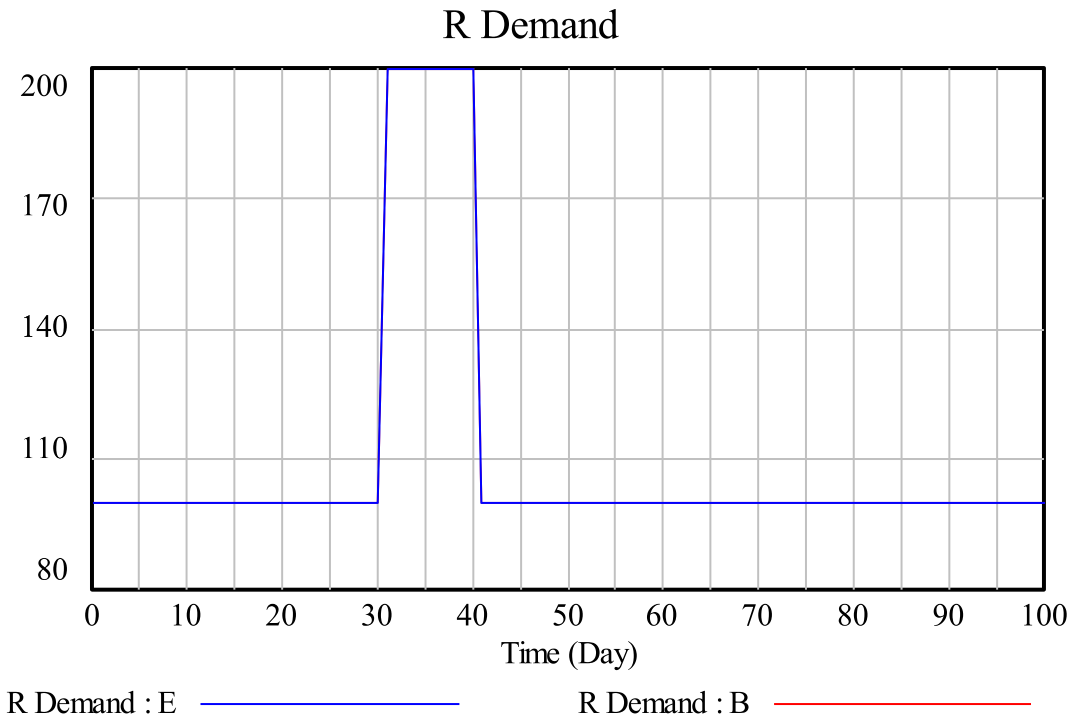
FINAL TIME = 100 ~ Day

INITIAL TIME = 0 ~ Day

TIME STEP = 1 ~ Day

The demand for R is the same for both B and E models. The following <Figure 10-2> is shown.

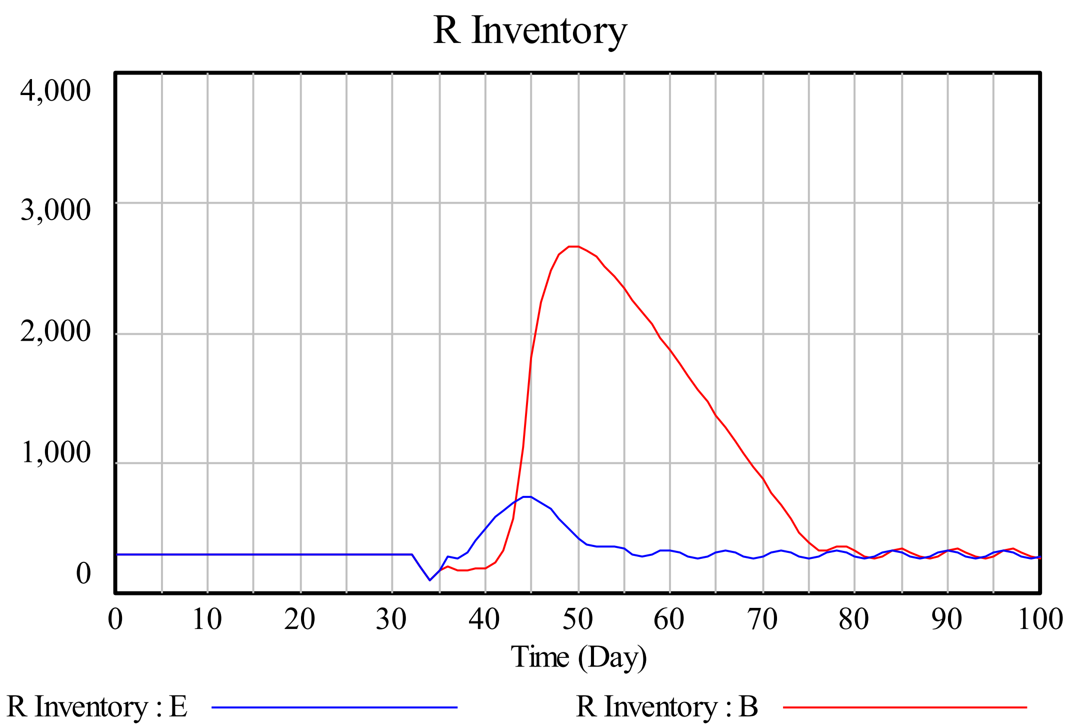
<Figure 10-2> Demand pattern for R



For demand 200 between 31 and 40 days, 100 are ordered from M, and the remaining 100 are ordered and received from S. S receives and responds to the demand that has come up through M more quickly. In the case of R, it is assumed that the lead time provided by M and the lead time provided by S are the same. In other words, shipping from S to R is special. This applies to special transports that occur only in emergency situations. In the model, the upper limit was set at 20%, and the range was ordered to M. It was modeled in case of day-to-day fluctuations.

When demand is <Figure 10-2> look at the results of models B and E. First, the measurement of R is shown in the following <Figure 10-3>.

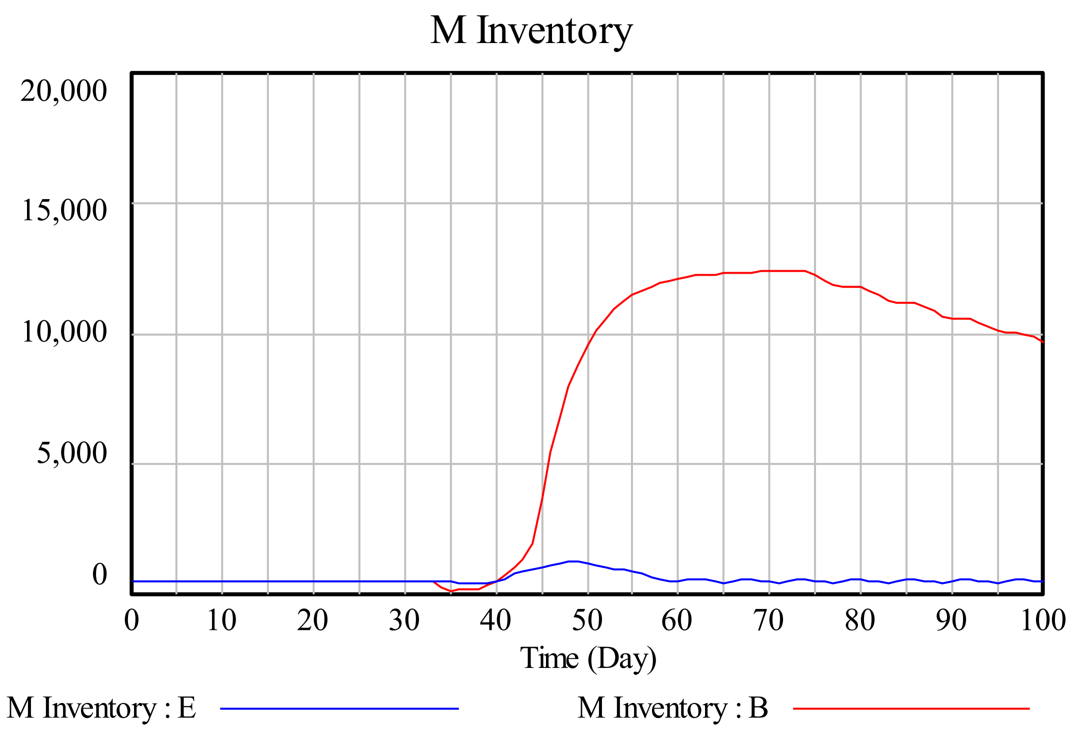
<Figure 10-3> Inventory comparison of R



Model B has an average of 739.05 stocks over 101 days. On the other hand, the R Inventory of the E model averages 33.18, which is less than half. The maximum value of inventory is 2,667 units to 734.79, which is one-third of the level. In terms of R shortfall (amount not delivered on a particular day), the Eahepfdl average is 2.592, compared to 11.18 for the B model. The B model is showing a much larger shortfall.

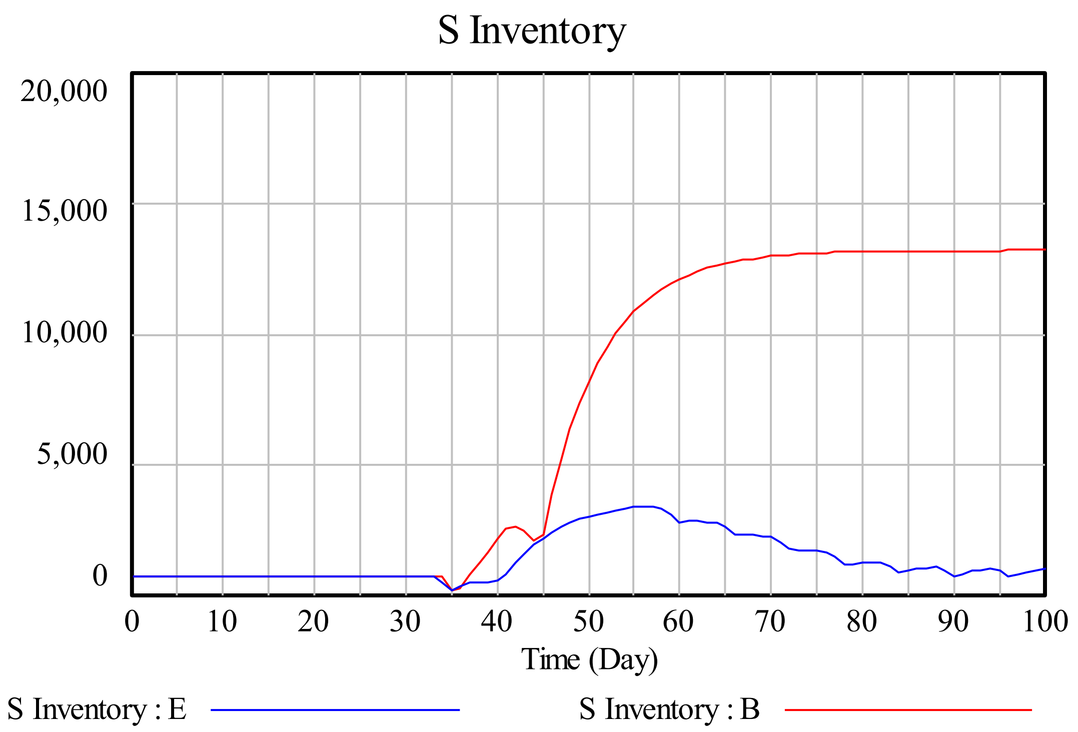
M The difference is even more stark in inventory.

<Figure 10-4> Comparison of M Inventory



The average daily inventory for model B is 6,305 units, compared to 580.39 for model E. At 100 days, the B model has not even reached equilibrium yet. A difference of more than 10 times appears in M inventory.

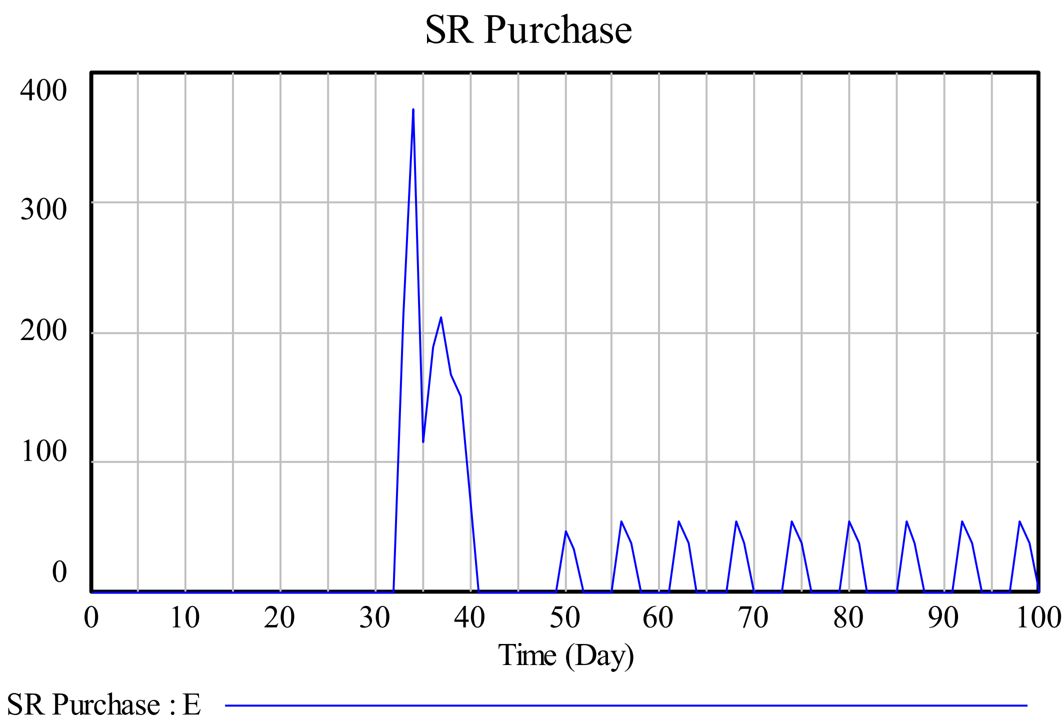
<Figure 10-5> Comparison of S inventories



The B model has an average of 6,972 S stocks, compared to only 1,395 S stocks for the E model. That's more than five times the amount. The maximum is 13,208 to 3,409. Here, too, there is a significant difference.

Finally, let's take a look at an additional burdensome part: SR Purchase.

<10-6> Time-dependent behavior of SR purchases



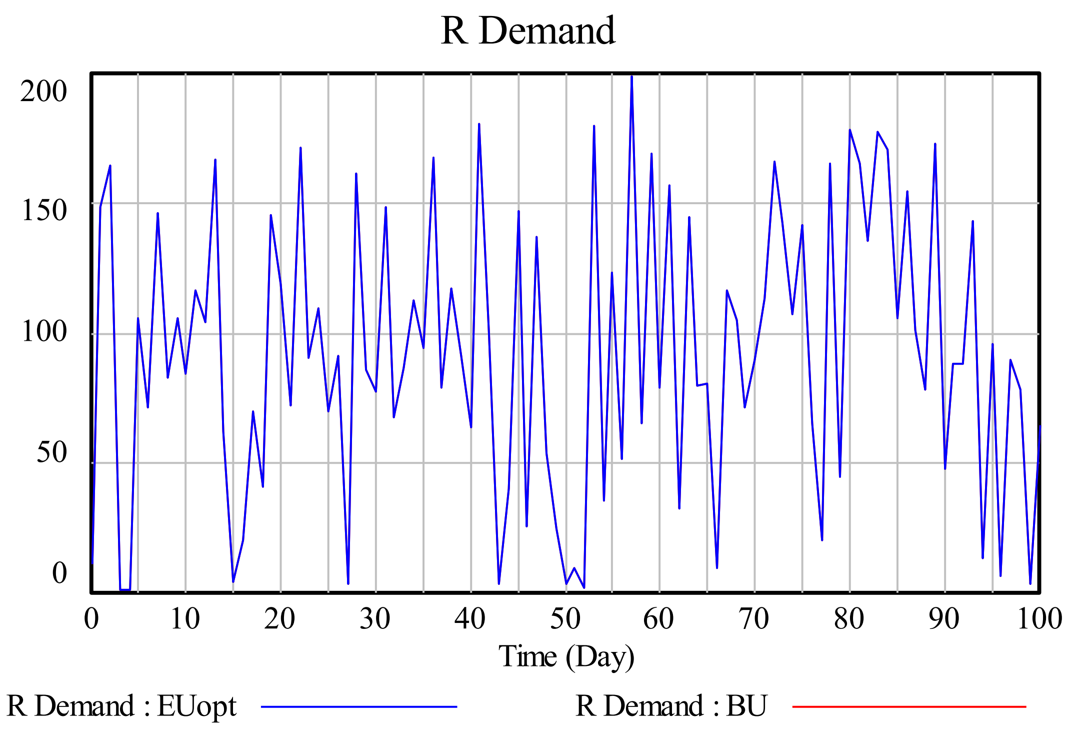
3 It is understandable that SR purchases occurred betweenthe 1st and 41st, but it is difficult to understand that a small positive number appeared afterwards. This is because after one major change, an order of R exceeded 20% of the usual demand 100. SR Purchase, that is, the use of emergency channels, is assumed to exceed 20% of the usual demand, where 20% is the decision maker's share. It is influenced by how the criteria for distinguishing between routine and large changes are determined.

The one-day average for SR Purchase is 22.79. The problem is that the maximum is 372.32, which means you have to have the ability to ship 372.32 pieces per day. The average is about 23, but to be able to deliver 372 is inevitable to cause inefficiencies in the use of transport modes. However, despite these inefficiencies, the difference in inventory is stark, so it would be advantageous to have an emergency channel if the interests of the entire supply chain are taken into account. There may be variables such as if the product is not bulky or by renting an external vehicle.

2) Effect of emergency channel when demand is uniform and constant

This time, we look at whether emergency channels are effective even when demand is:

<Figure 10-7> R demand at a daily distribution and constant



Constant here means no trend. The average of 100 remains the same.

R When demand is constant and distributed, sometimes less and sometimes more, orders are placed from upstream supply chain participants. At this time, the supply chain (E model) with an emergency channel is designed to set a reference point, use the emergency channel only for quantities greater than that value, and order M for values below that standard.

Cost variables were added to try to optimize.

Total Cost = Transport Cost+Inventory Cost

Transport Cost = (INTEGER(M Purchase)+1+INTEGER(R Purchase)+1+INTEGER(S Purchase)+1+INTEGER(SR Purchase)+1)*100

Inventory Cost = (M Inventory+R Inventory+S Inventory)*1

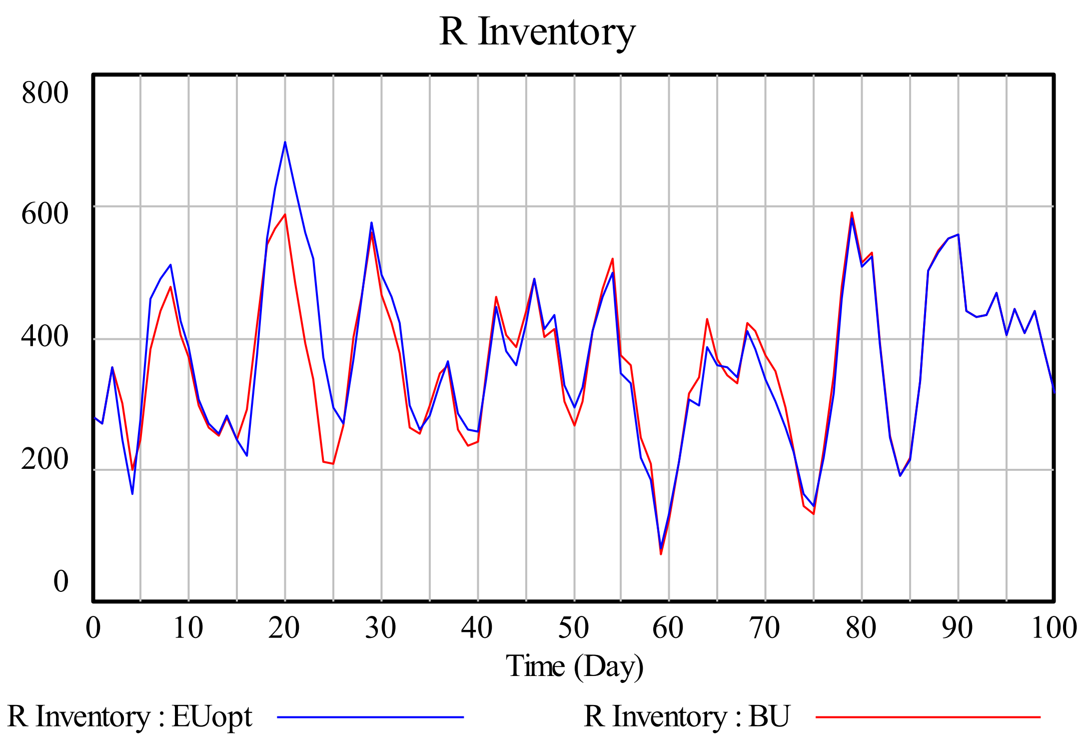
Shortage Cost = 2*R Shortage Rate

In the E model, the transportation cost is based on 100 for each participant's purchase, and one for less than 100 and two for more than 100. Each transport truck costs $100. The inventory maintenance cost was assumed to be $1 per day from each participant's inventory, and the inventory maintenance cost was assumed to be $2 per day only for R's inventory shortage.

In Model B, transportation costs for SR purchases are not included. All the rest were applied in the same way as the E model.

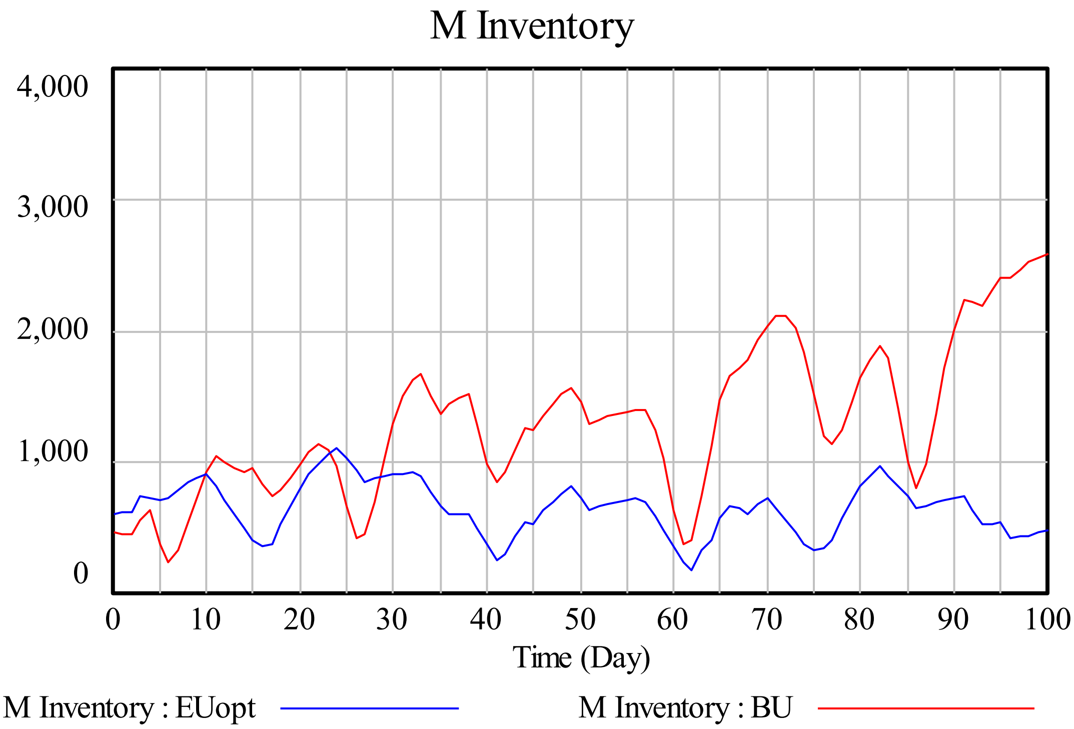
We then obtained the Upper Index value, which minimizes the total cost. Its value was 0.588755. The data file of the model with this value applied was named EUopt. The result of applying the R demand of the one-positive distribution to the B model is expressed as BU.

<Figure 10-8> R Inventory of Constant Demand for Monolithic Distribution



R Inventory shows similar values for both models. B U is 360.69 on average and EUopt (when the EU model is applied with an upper index that minimizes total cost) is 367.86. It's a tiny value, but rather the EU model has more R inventory.

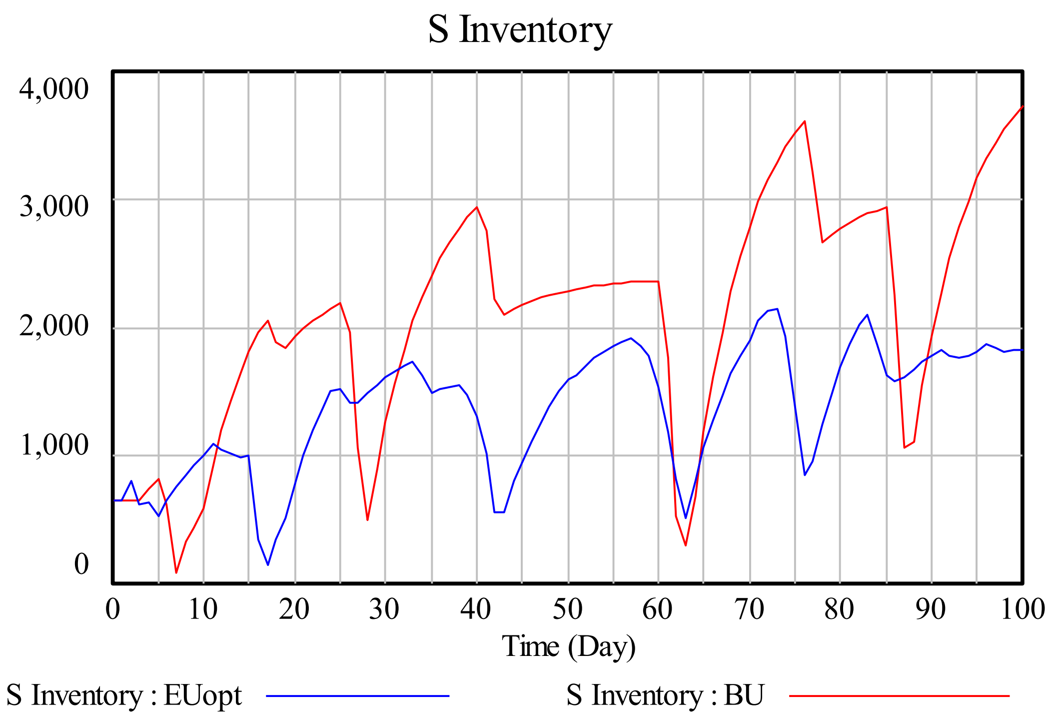
<Figure 10-9> M Inventory of Constant Demand for Monotonic Distribution



M inventory is markedly different. The BU model's M inventory averaged 1,300 units, while the EUopt fell by less than half to 647.92. This is probably because S handles some of it.

In the case of S, the burden was increased because orders from M and R were processed. The inventory of S is shown in the following figure.

<Figure 10-10> S Inventory of Constant Demand for Distribution



S inventories were much lower than expected in the EU model. The average EUopt was 1,363, compared to 2,075 BU, a difference of more than 50%. It shows that even if S performs services for R and M at the same time, it may show lower inventory levels. Of course, this is the positive effect of the emergency channel.

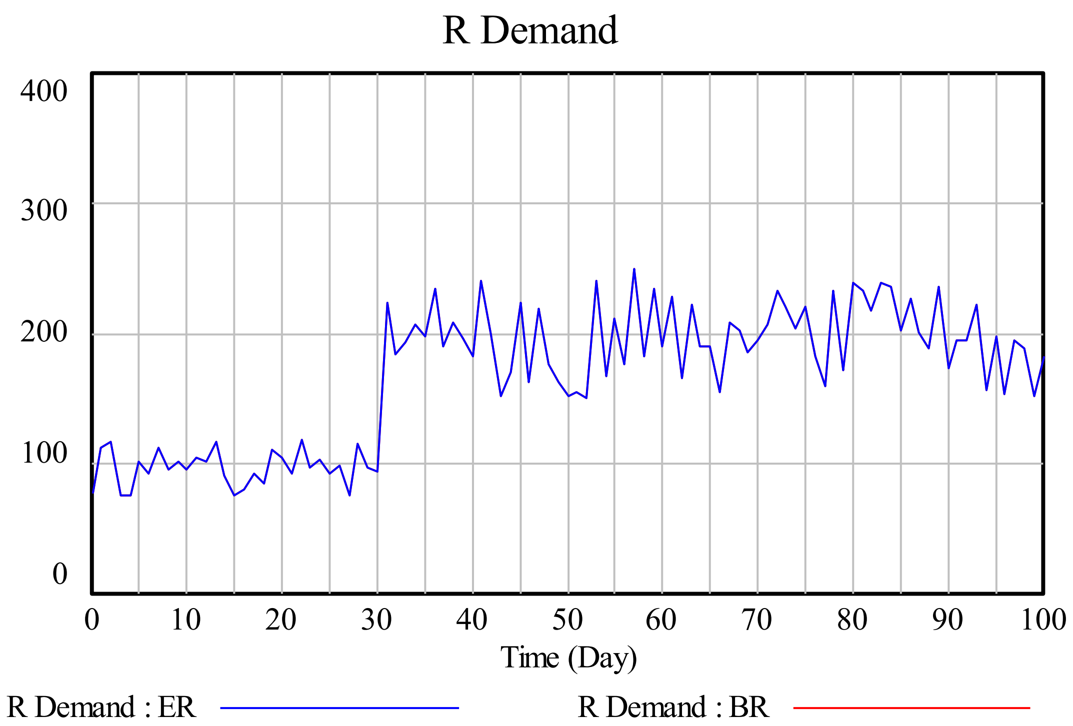
Look at it in terms of total cost. The transportation cost was EUopt = 23,419 and BU = 34,074, so if there was an emergency channel, the transportation cost was lower. This is because there are many cases where M is more than 2 units in the middle. The maximum value of BU's R Purchase value was 462.60, which was calculated to require five trucks. In the EU model, the required transport truck is stabilized to about one, while in the BU model, the deviation is large, sometimes up to five. In terms of inventory shortage costs, BU=0.8836 and EUopt=1.1013 caused slightly more in the EU. The difference does not appear to be significant. This is because the standard deviation is very large, about 8. In terms of inventory maintenance costs, EUopt was relatively small at 2,379 and 3,736.

Even in supply chains with no major changes, only routine changes, emergency channels show that they work. It was found to be optimal if R gave a demand share of approximately 25% for S. Since this index varies depending on price or cost constants, it cannot be concluded that it is 25%. After running the simulation, you need to find the enemy.

3) Emergency Channel and Resilience

Look at whether emergency channels will provide resilience to the supply chain. Assume the following demand:

<Figure 10-11> Demand patterns for resilience



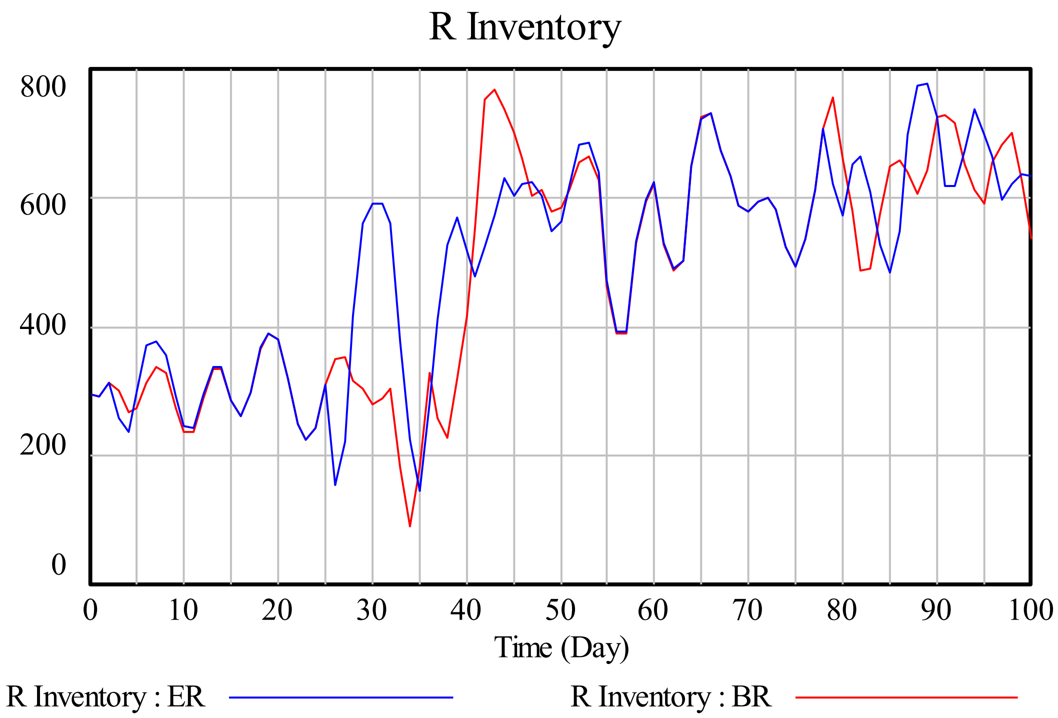
The BU and EU models used earlier generated the above demand and changed the model names to BR and ER. The ER model applied an Upper Index value (0.60073) that minimizes the total cost. To express R Demand as shown in <Figure 10-11> enter the relation as follows.

R Demand = (Demand Average+STEP(Demand Average, 31))*RANDOM UNIFORM(0.75, 1.25, 2345)

This demand shows rapid change. On a 31-day basis, demand doubles on average. It has a significant impact on the supply chain.

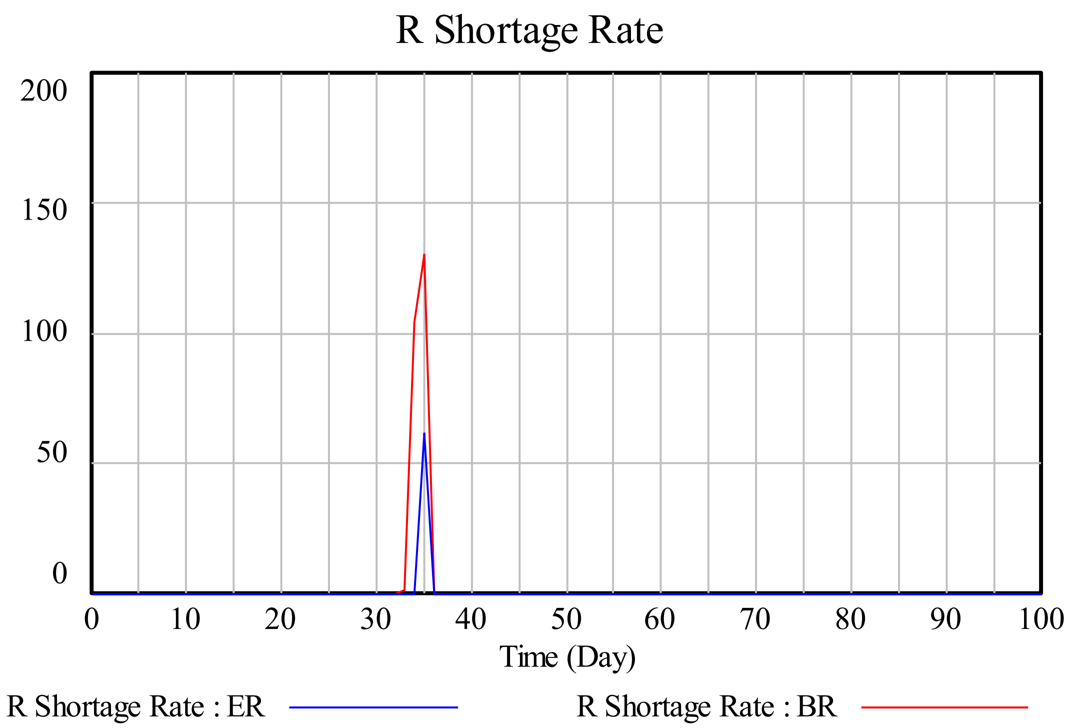
In order to further emphasize resilience in the process of minimizing total costs in ER, a unit shortfall cost of $9 was assumed. As much as possible, R has been optimized to avoid running out of stock.

<Figure 10-12> R Inventory comparison



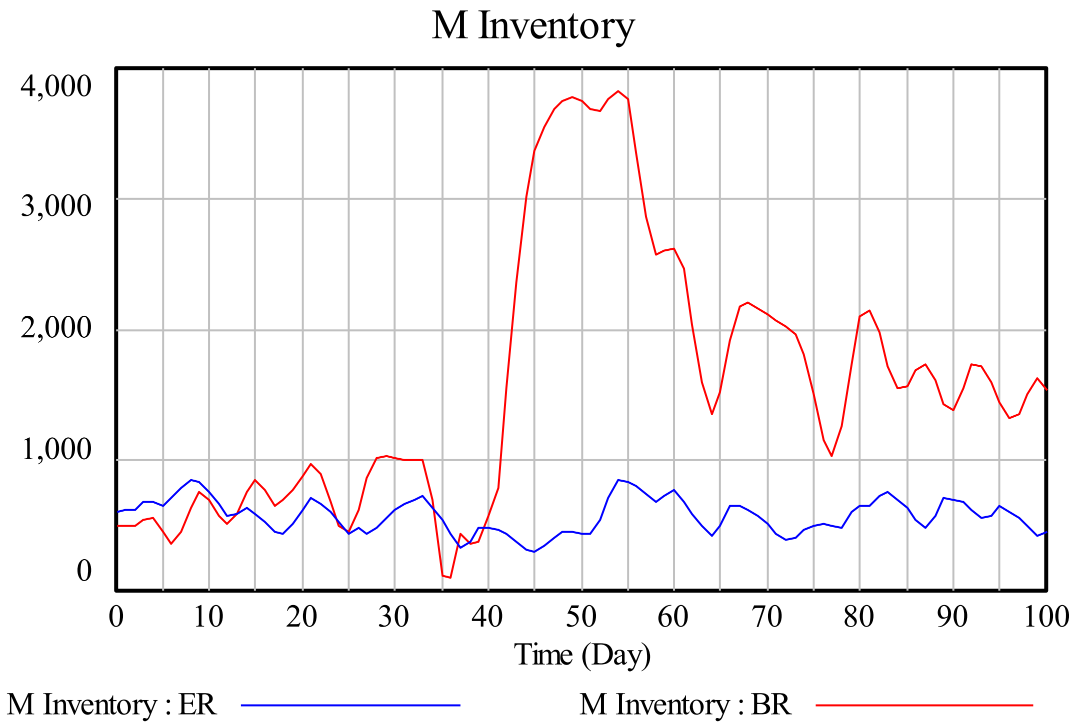
BR has an average of 482.51 inventories and ER has an average of 498.21, indicating that BR's inventory is slightly small. On the other hand, R's stock shortage is shown in the following figure. After the 31st, both models will have a shortage.

<Figure 10-13> R Shortage Rate Comparison



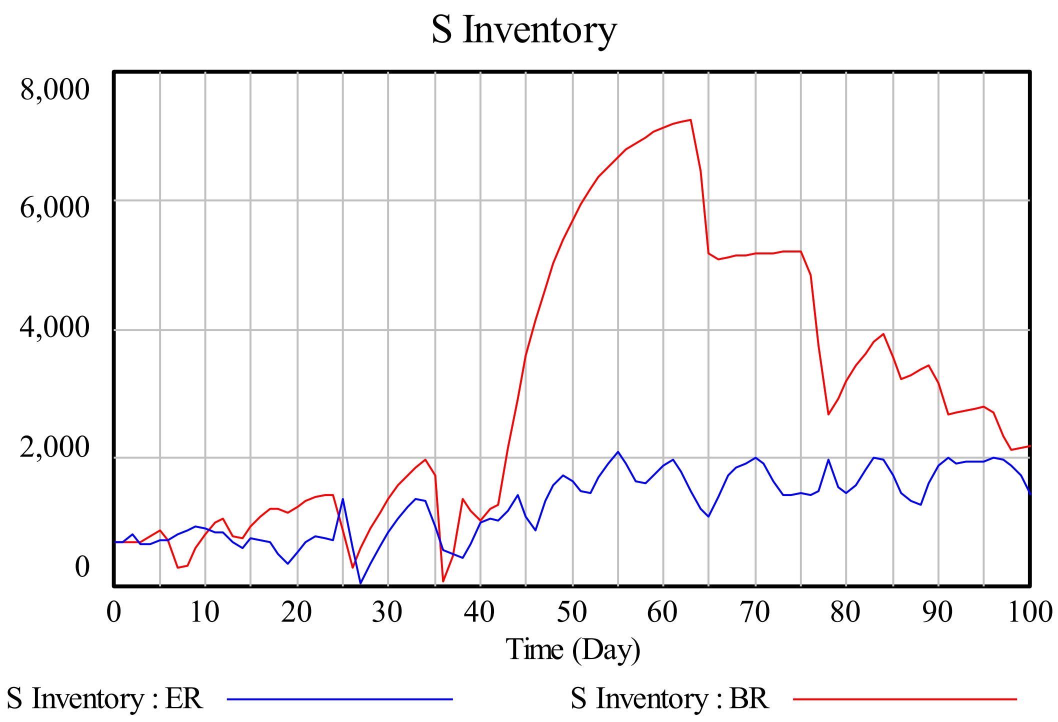
The shortfall of R was up to 130 BRs, compared to 61 ERs. It is judged that the responsiveness of E R is more than twice as good.

<그림 10-14> BR과 ER의 M Inventory



BR and M Inventory are red lines. This line increases and decreases to a very large value after the 31st. The whip effect occurs clearly. In comparison, it can be confirmed that ER (blue line) rarely causes a whiplash effect. The average M Inventory for BR is 1,557, compared to 573 for ER, which shows that it is acceptable to have a very small amount.

<그림 10-15> BR과 ER의 S Inventory



The average for S Inventory is 3,029 BRs, compared to 1,272 ERs, which is less than half. In terms of total cost, the BR is $59,240 and the ER is $46,057, indicating that the ER is also superior in terms of cost.

Therefore, it was seen that having an emergency channel could create a resilient supply chain at a lower cost. Depending on the size of the sudden change, lead time, and various cost constants, the effect of the emergency channel varies. You should use an emergency channel strategy that is appropriate for each situation. However, here only the possibility of an emergency channel is suggested.

1Chapter 1

Supply chain design for lead time pooling

Supply Chain Design with Leadtime Pooling

1) Basic understanding of the two models

Pooling refers to the phenomenon that gathering in one place reduces uncertainty. When there is uncertainty in one place (e.g., deviation in demand) and uncertainty in the other, it means that if you put the uncertainty in both places together, it will be smaller than the individual uncertainties. The size of the reduction is determined by the Square Principle. This is done under the assumption that it is a normal distribution.

When designing a supply chain, pooling effects can be considered as a factor that must be considered because they can lead to consequences in a form that is different from common sense. After all, supply chains should be seen as coping with uncertainty.

In this chapter, simulations are conducted with two supply chains. One consists of three stages (echelon). It consists of producers (M), distributors (D), and retailers (R). There is one producer and one distributor. On the other hand, there are 100 retailers.

Another supply chain consists of two phases. It takes the form of direct delivery from the producer to the retailer. There is no distributor in the middle.

The producer is a bit far from the retailer. In Phase 2, it takes an average of 36 hours for 1 00 retailers to place orders and receive goods from producers. It takes a day and half a day more. In the two-stage model, because it is delivered to the producer , the time distance between the retailer and the producer is 36 hours. On the other hand, in the three-stage supply chain, a distributor is set up near the retailer. The lead time between distributors and producers is 36 hours, but the time distance between distributors and retailers is reduced to 1 hour.

The cumulative lead time for each supply chain is 45 hours for the third stage supply chain and 44 hours for the second stage supply chain. According to L'ittle's Law, inventory is calculated by the total cumulative lead time times hourly receipts (or shipments), resulting in one hour more inventory in the third-tier supply chain.

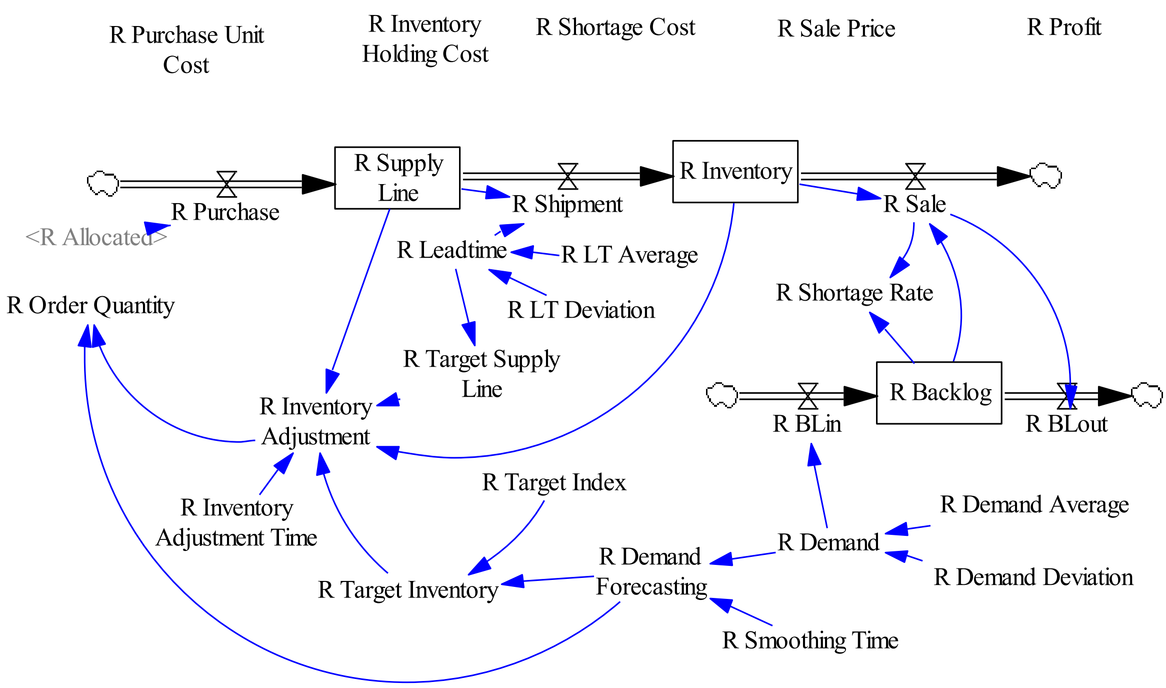
However, given the pooling effect discussed earlier, inventories in the third-tier supply chain may shrink further. The margin structure of inventory maintenance costs , inventory shortage costs, and purchases and prices determine the benefits of the supply chain. Depending on these parameters, whether to choose step 3 or step 2 varies. Here, I would like to present an example contrary to common sense, that if the step or lead time is longer, the inventory will increase, which will penalize profits. However, he did not choose an absurd parameter value.

A producer buys something for $2 and supplies it to a distributor or retailer for $4. Tier 3 distributors buy for $4 and sell to retailers for $6. Retailers buy it for $4 or $6 and sell it for $10. The cost of maintaining one unit of inventory for one hour was assumed to be $0.001. The same applies to both retailers and producers. If there is an inventory shortage cost, it is assumed that the shortfall cost per unit is $4. For Phase 2 supply chains, it is $6, but for direct comparison, the shortfall cost for both models is limited to $4. When a retailer visits and is out of stock, this customer does not result in a demand loss (backlogged). Instead, an hour's delay is assumed to cost $4 in penalties. In this setup, the two supply chains try to hold as much inventory as possible. But we don't have infinite lots. This is because although the cost of maintaining inventory is a very small value per unit of time, it can be reversed when it exceeds a certain value.

2) Supply chain modeling with subscripts

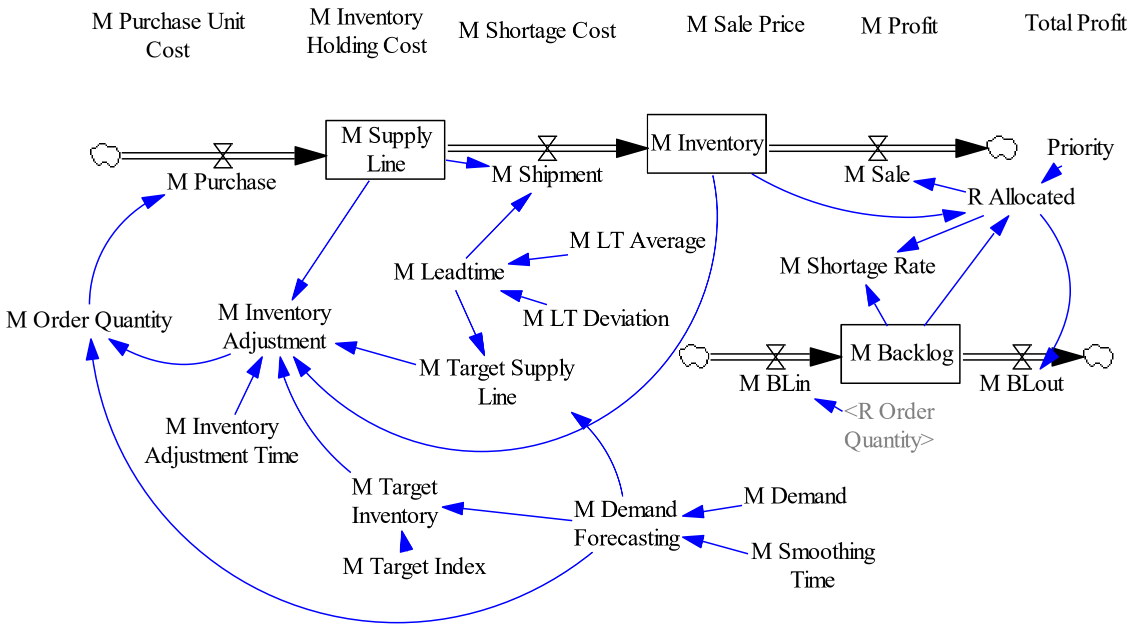
Build two models. The Phase 3 model was named T3e.mdl (arbitrarily) and the Phase 2 model was named T2e.mdl. Because it utilizes subscripts, the model becomes relatively complex. Therefore, it is explained mainly in the T2e model.

<Figure 11-1> Retailer (R) portion of the two-step model



The modules for basic inventory management are the same for both producers (including distributors in the three-step model).

<Figure 11-2> Producer (M) portion of the two-step model



I hid a lot of arrows because of the complexity. The following relation can be seen to understand its structure.

Inventory Holding Cost=0.001

M Backlog[Retailer]= INTEG (M BLin[Retailer]-M BLout[Retailer],100)

M BLin[Retailer]=R Order Quantity[Retailer]

M BLout[Retailer]=R Allocated[Retailer]

M Demand Forecasting=SMOOTH(M Demand, M Smoothing Time)

M Demand=SUM(R Order Quantity[Retailer!])

M Inventory Adjustment Time=M LT Average

M Inventory Adjustment=(M Target Inventory-M Inventory+M Target Supply Line-M Supply Line)/M Inventory Adjustment Time

M Inventory Holding Cost=Inventory Holding Cost

M Inventory= INTEG (M Shipment-M Sale,M Target Inventory)

M Leadtime=RANDOM NORMAL(1, M LT Average*2, M LT Average, M LT Deviation, 5678)

M LT Average=8

M LT Deviation=SQRT(M LT Average)

M Order Quantity=MAX(0, M Demand Forecasting+M Inventory Adjustment)

M Profit=-M Inventory*M Inventory Holding Cost-M Purchase*M Purchase Unit Cost+M Sale*M Sale Price

M Purchase Unit Cost=2

M Purchase=M Order Quantity

M Sale Price=4

M Sale= SUM(R Allocated[Retailer!])

M Shipment=M Supply Line/M Leadtime

M Shortage Cost=Shortage Cost

M Shortage Rate[Retailer]=MAX(0, M Backlog[Retailer]-R Allocated[Retailer])

M Smoothing Time=8

M Supply Line= INTEG (M Purchase-M Shipment,M Target Supply Line)

M Target Index=0

M Target Inventory=M Demand Forecasting*M Target Index

M Target Supply Line=M Leadtime*M Demand Forecasting

Priority[Retailer]=1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1, 1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1, 1,1,1,1,1,1,1,1,1,1

R Allocated[Retailer]=ALLOCATE BY PRIORITY(M Backlog[Retailer], Priority[Retailer], 100, 10, M Inventory)

R Backlog[Retailer]= INTEG (R BLin[Retailer]-R BLout[Retailer],R Demand Average[Retailer])

R BLin[Retailer]=R Demand[Retailer]

R BLout[Retailer]=R Sale[Retailer]

R Demand Average[Retailer]=100

R Demand Deviation[Retailer]=10

R Demand Forecasting[Retailer]=SMOOTH(R Demand[Retailer], R Smoothing Time[Retailer])

R Demand[Retailer]=RANDOM NORMAL(0, R Demand Average[Retailer]*2, R Demand Average[Retailer], R Demand Deviation[Retailer], 1234)

R Inventory Adjustment Time[Retailer]=R LT Average[Retailer]

R Inventory Adjustment[Retailer]=(R Target Inventory[Retailer]-R Inventory[Retailer]+R Target Supply Line[Retailer]-R Supply Line[Retailer])/R Inventory Adjustment Time[Retailer]

R Inventory Holding Cost[Retailer]=Inventory Holding Cost

R Inventory[Retailer]= INTEG (R Shipment[Retailer]-R Sale[Retailer],R Target Inventory[Retailer])

R Leadtime[Retailer]=RANDOM NORMAL(1, R LT Average[Retailer]*2, R LT Average[Retailer], R LT Deviation[Retailer], 2345)

R LT Average[Retailer]= 36

R LT Deviation[Retailer]=6

R Order Quantity[Retailer]=MAX(0, R Demand Forecasting[Retailer]+R Inventory Adjustment[Retailer])

R Profit[Retailer]=-R Inventory[Retailer]*R Inventory Holding Cost[Retailer]-R Purchase[Retailer]*R Purchase Unit Cost[Retailer]+R Sale[Retailer]*R Sale Price[Retailer]-R Shortage Cost[Retailer]*R Shortage Rate[Retailer]

R Purchase Unit Cost[Retailer]=4

R Purchase[Retailer]=R Allocated[Retailer]

R Sale Price[Retailer]=10

R Sale[Retailer]=MIN(R Backlog[Retailer], R Inventory[Retailer])

R Shipment[Retailer]=R Supply Line[Retailer]/R Leadtime[Retailer]

R Shortage Cost[Retailer]=Shortage Cost

R Shortage Rate[Retailer]=MAX(0, R Backlog[Retailer]-R Sale[Retailer])

R Smoothing Time[Retailer]=8

R Supply Line[Retailer]= INTEG (R Purchase[Retailer]-R Shipment[Retailer],R Target Supply Line[Retailer])

R Target Index[Retailer]=RTargetIndex

R Target Inventory[Retailer]=R Demand Forecasting[Retailer]*R Target Index[Retailer]

R Target Supply Line[Retailer]=R Leadtime[Retailer]*R Demand Average[Retailer]

Retailer:R1,R2,R3,R4,R5,R6,R7,R8,R9,R10,R11,R12,R13,R14,R15,R16,R17,R18,R19,R20,R21R22,R23,R24,R25,R26,R27,R28,R29,R30,R31,R32,R33,R34,R35,R36,R37,R38,R39,R40,R41,R42,R43,R44,R45,R46,R47,R48,R49,R50,R51,R52,R53,R54,R55,R56,

R57,R58,R59,R60,R61,R62,R63,R64,R65,R66,R67,R68,R69,R70,R71,R72,R73,R74,R75,R76,R77,R78,R79,R80,R81,R82,R83,R84,R85,R86,R87,R88,R89,R90,R91,R92,R93,R94,R95,R96,R97,R98,R99,R100

RTargetIndex=7

Shortage Cost=4

Total Profit=M Profit+SUM(R Profit[Retailer!])

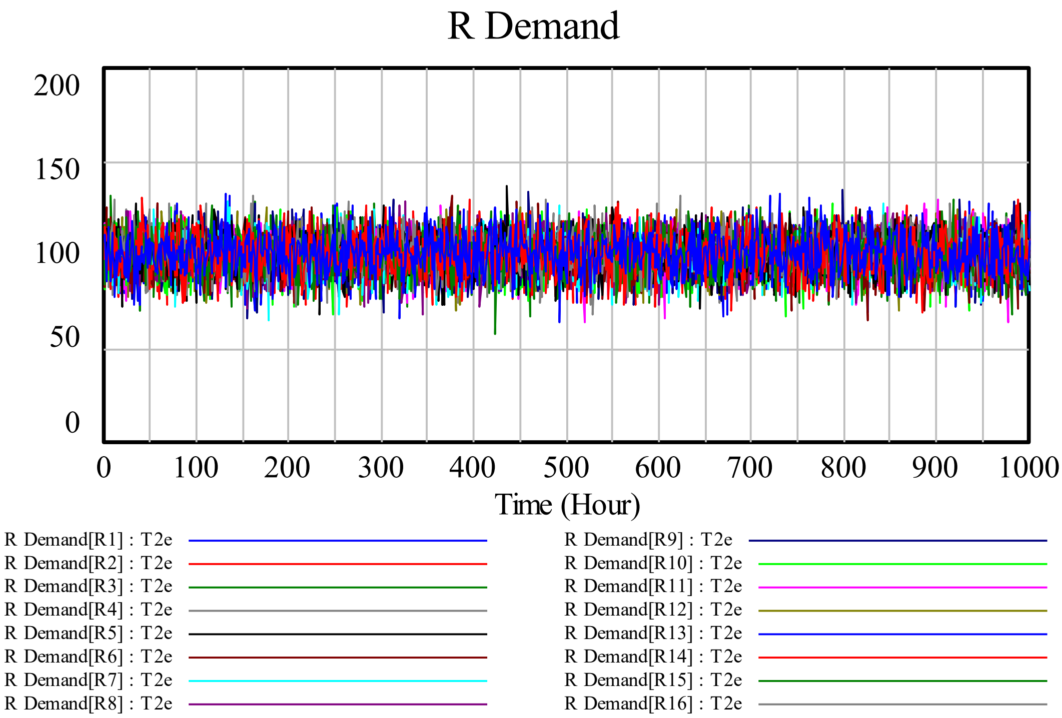
FINAL TIME = 1000

INITIAL TIME = 0

TIME STEP = 1

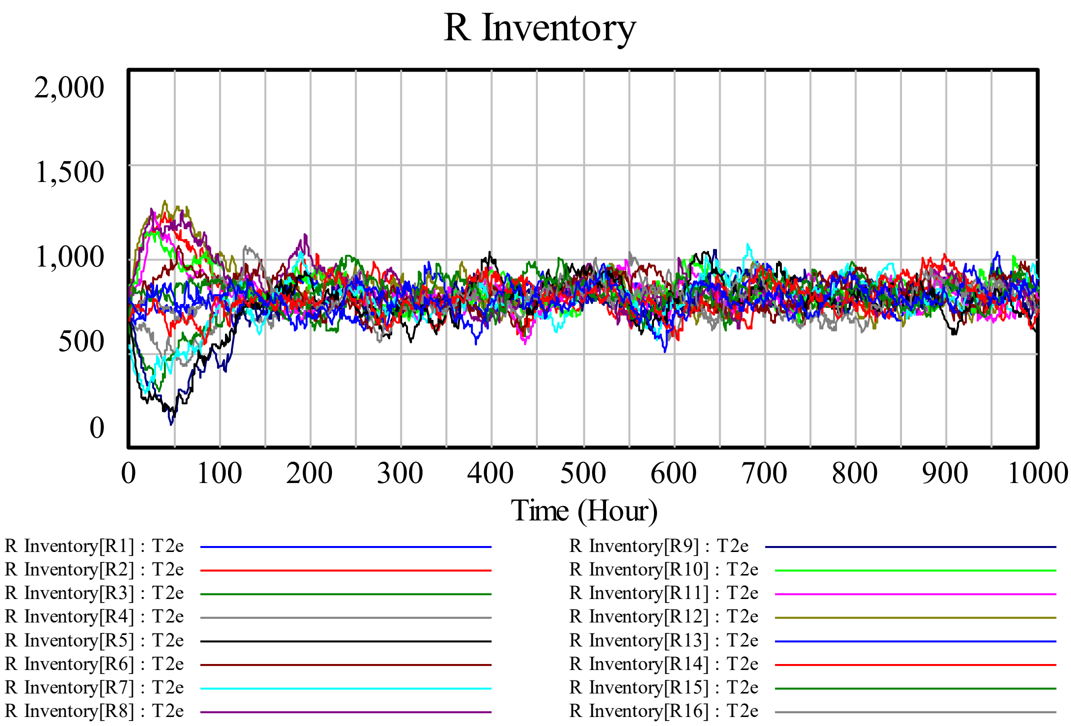
Setting up a subscript is not easy. Retailers operate as subs, and producers operate based on the aggregated demand. The names of the subscripts were given as Retailer, and each retailer was named S 1 through S100. Each retailer was set to generate demand at 100 per hour and 10 standard deviations. The hardest part is deciding how much producers ship to retailers. Here, we used a function called Allocation By Priority. It was assumed that each person's attractiveness, etc., was the same. Each of the 100 retailers was to receive goods according to equal priority .

<Figure 11-3> Retailer Demand Generation in Phase 2 Model (Only 16 Retailers Presented)



Retail demand occurred in a normal distribution with an average of 100 standard deviations around 100.

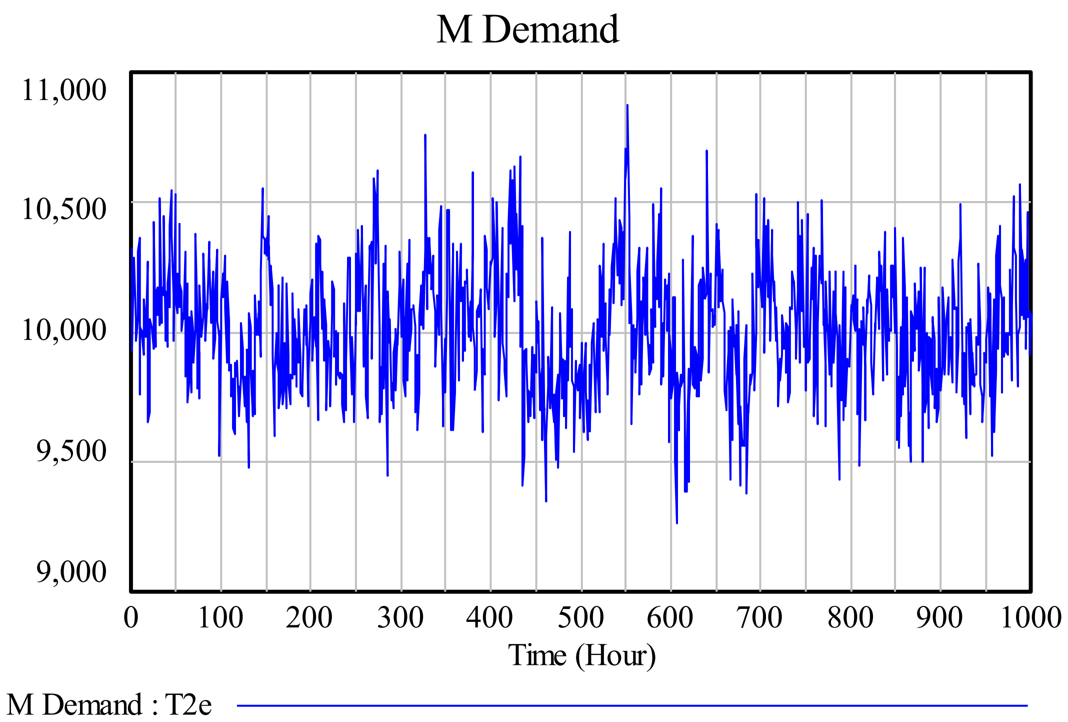
<Figure 11-4> Retailer's inventory of a two-stage model



At the beginning, there are high and low inventories, and after about 100 days, they enter a certain area. This can be seen as an initial effect in the simulation. The analysis excludes enough time.

The quantity ordered from 100 retailers is the demand for M.

<Figure 11-5> M Demand in Phase 2 Model



Because random random numbers have been generated, the demand mean of M is not exactly 10,00zeros. An average of 10,012 came out, with a minimum of 9,264 and a maximum of 10.875. The demand for R is around 100 on average, and the minimum maximum price is about plus or minus 30%, while the demand for M is within 10%. This is because of pooling. This is because when the order volume of one retailer is high, the probability that the order volume of another retailer is high at the same time decreases.

Here, the index that adjusts the target inventory of retailers (RTargetIndex), which maximizes total profit, and the index that adjusts the target inventory of recontractors (M Target Index) are optimized. As a result of the optimization, the adjustment index for retailers was 7, and the target inventory adjustment index for manufacturers was 0. This means that manufacturers don't have to have safety stock. For reference, the adjustment index in the three-step model is as follows. In parentheses are the optimal parameters in the two-step model. These are numbers rounded to the nearest 1.

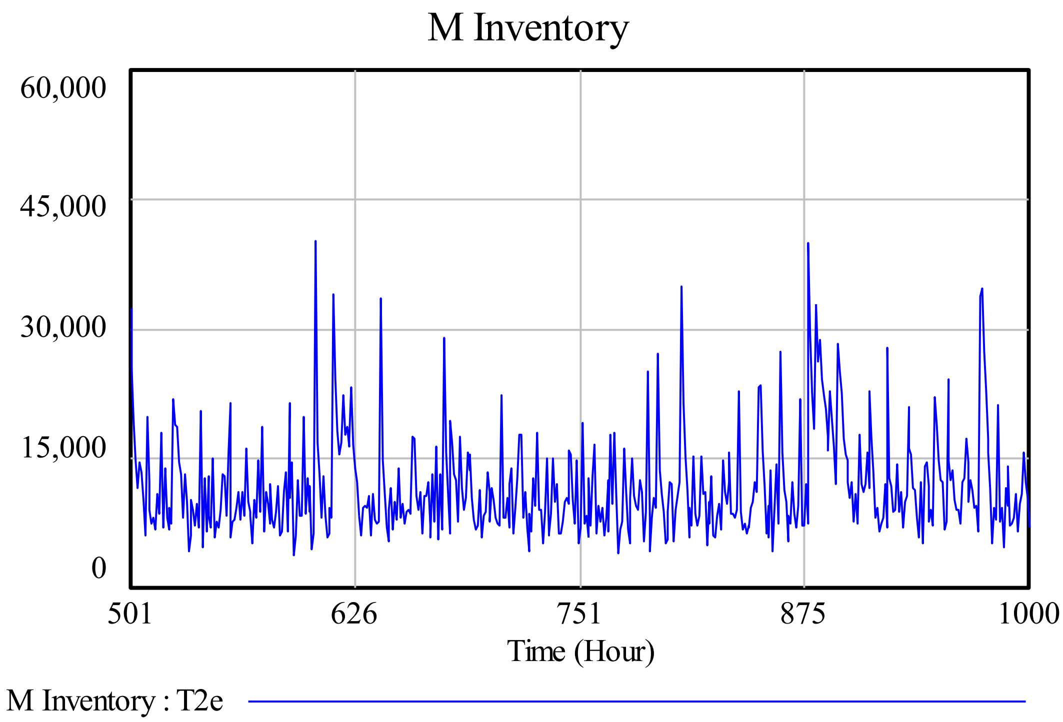
M Target Index =0(0)

D Target Index =2

R Target Index=7(7)

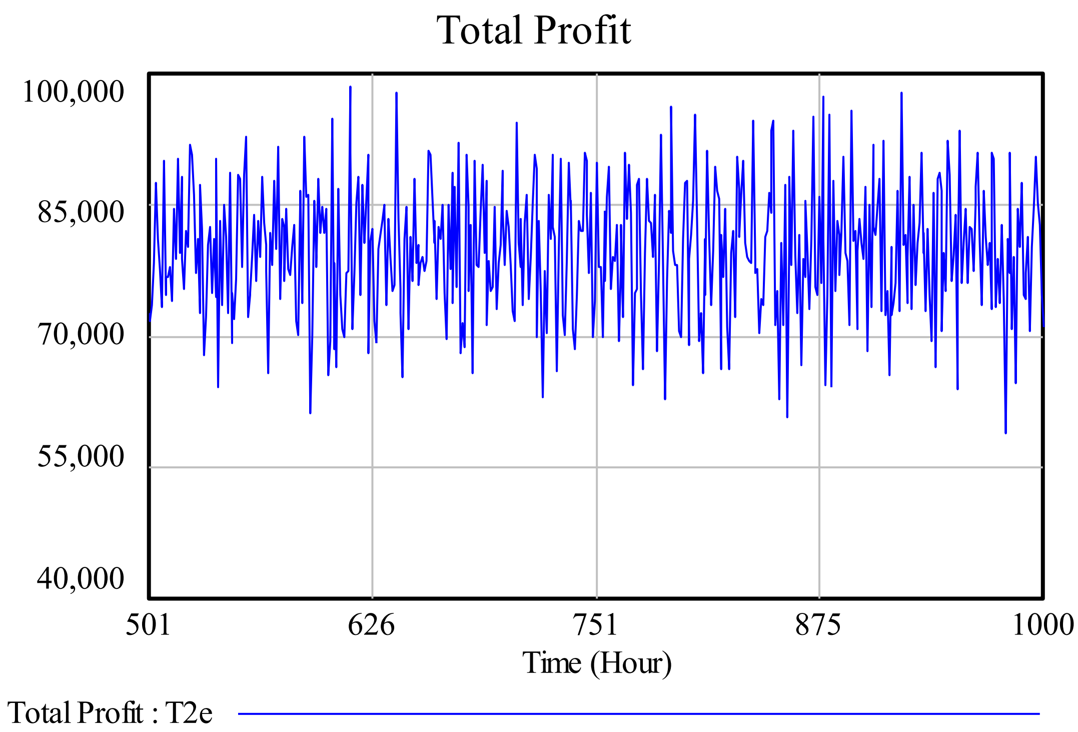
The manufacturer's inventory accordingly is shown in the following figure.

<Figure 11-6> Manufacturer (M) inventory of the two-stage model



Manufacturers have an average of 11,817 inventories for 500 hours from 501 to 1,000 hours, with a minimum of 3,857 and a maximum of 40,125.

<11-7> Total Profit in Phase 2 Model

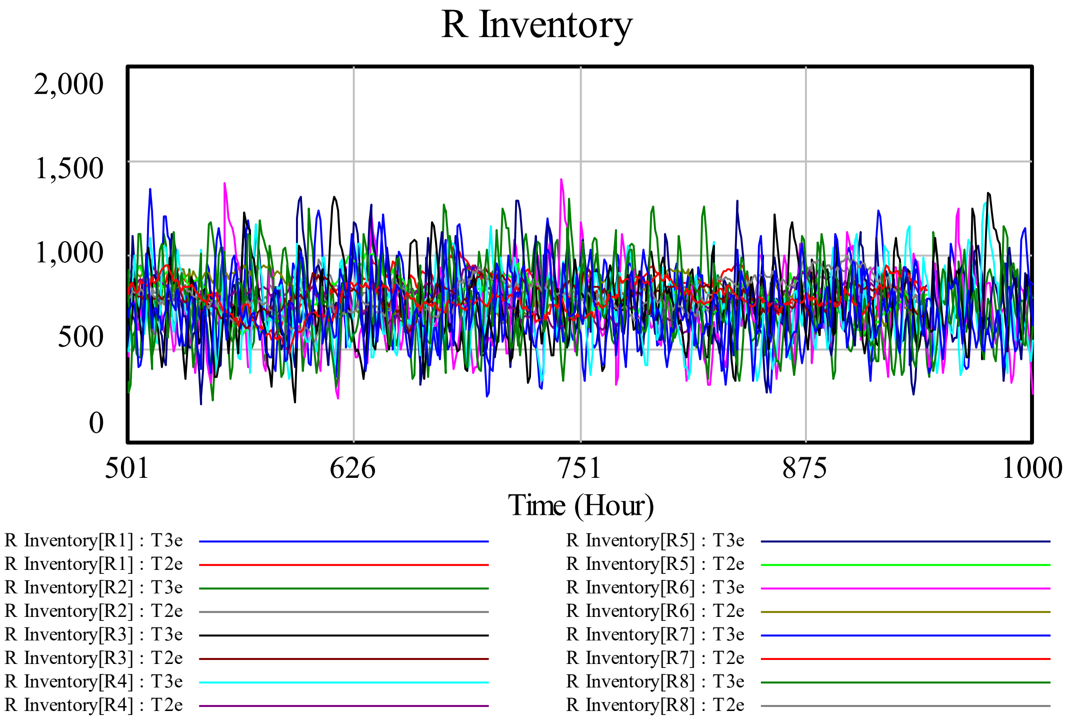


The second-stage supply chain has a profit of $79,902 per hour, with a minimum profit of $58,904 and a maximum of $98,442. The parameters used are described at the beginning of this chapter. Gross profit does not include the cost of understocking due to the producer's (M) shortage.

3) Comparison with the three-step model

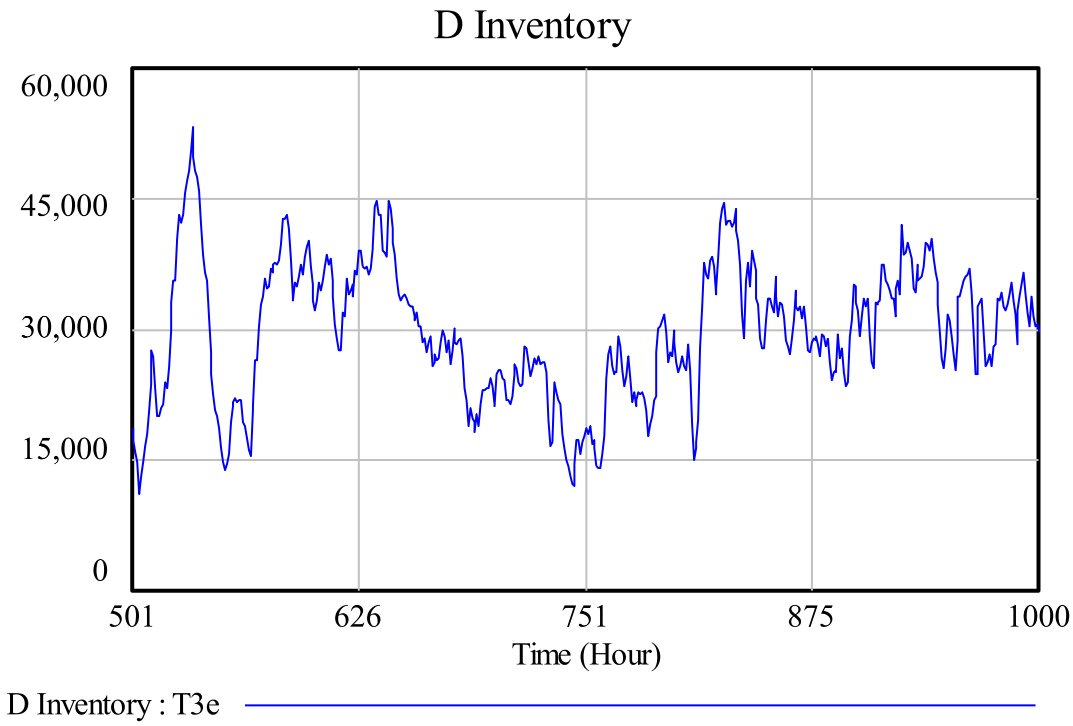
You can create a model by including a distributor (D) in the middle of the two-step model.

<Figure 11-8> R inventory of Phase 2 and Phase 3 models



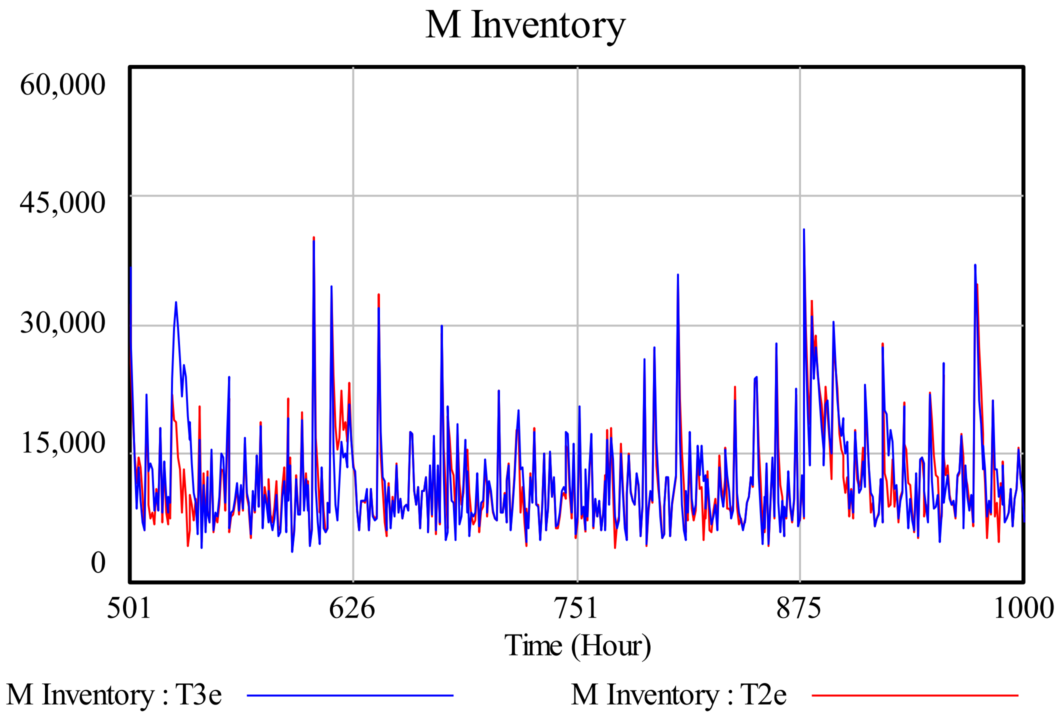
Both models aim for 7 hours of inventory, so they have similar levels of inventory. Still, because of the lead time, the retail inventory in the Phase 2 model is larger than in Phase 3. There are variations depending on the retailer, for example, in R1, Phase 2 has an average inventory of about 793 units, while in the Phase 3 model it comes out around 710. For R2, it comes out 805 to 743. There is an average difference of about 60.

<Figure 11-9> D inventory of a three-step model



Since there are no distributors in the two-stage model, the figure above occurs only in the three-stage model. For 500 days, they have 29,687 per hour, as few as 11,053 and as many as 53,334.

<Figure 11-10> Manufacturer inventory of the two models



The blue line is the three-step model, and the red line represents the manufacturer's inventory of the two-stage model. The average inventory of the three-stage model is 11,966 units, and the second-stage model is 11,817, a very narrow difference. Both models have similar results because they do not have a safety stock.

Total profit averages $80,360 per hour for the three-stage model and $79,902 for the two-stage model. Common sense suggests that the three-stage model is much more expensive and therefore the gross profit is lower, but simulation results show that the three-stage model is marginally superior but better. The result is, of course, the effect of pooling.

1Chapter 2

Product Strategy and Supply Chain Management

Product Strategies in the Supply Chain

1) Modeling of product strategy

Let's define strategy as an action plan with intent. There are differentiation strategies , cost advantage strategies, and centralization strategies, and if differentiation strategies are further subdivided, they can be divided into various categories such as function differentiation and service differentiation. Here, we look at four strategies, focusing on activities that affect the demand for a product.

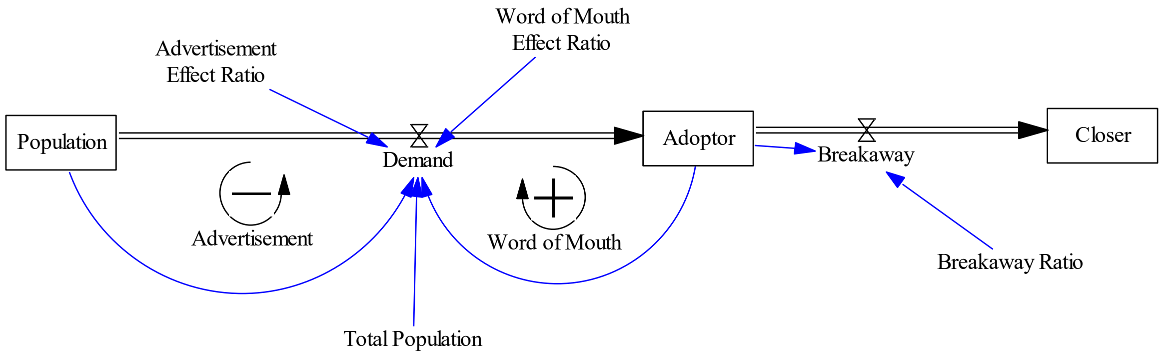
<Table 12-1> 4 Product Strategies

Hereafter		
InDV	Ad-oriented strategy	Defined as a strategy that focuses on advertising activities to increase demand.
WOM	Oral Effect Strategy	Strategies to increase the word of mouth effect by maintaining high quality or strategies that actively utilize network sales
DUO	Dual Strategy	A strategy that pursues both an advertising-oriented strategy and an oral effect strategy. Due to resource constraints, it is less effective than ADV and less effective than WOM. Both strategies are more effective than NOS.
NOS	Strategy	No strategy.

- There are also various product strategies.

Depending on the product strategy, demand varies. To simplify this, we created the following model.

<Figure 12-1> Product Strategy and Demand Model



Total Population=40,000

Population=INTEG(-Demand, Total Population-Adaptor-Closer)

Adopter=INTEG(Demand-Breakaway, 1)

Closer= INTEG(Breakaway, 0)

Advertisement Effect Ratio = 0.01 등

Word of Mouth Effect Ratio = 0.01 등

Breakaway Ratio=0.01

Demand=MAX(0, Population * Advertisement Effect Ratio + Adopter * Word of Mouth Effect Ratio* Population/Total Population)

We need to take a closer look at the Demand relation. Population multiplied by the Advertising Effect Ratio is included in demand. There are 40,000 people and 0.1% want to buy products a day through advertising. And the rate at which an adopter encourages an adopter to buy the product is expressed as the Population/Total Population*Word of Mouth Effect Ratio. When an adopter meets with four people in a day, the probability of recommending a Population to buy them is the Word of Mouth Effect Ratio.

Then, according to the four strategies, the parameters were set differently as follows.

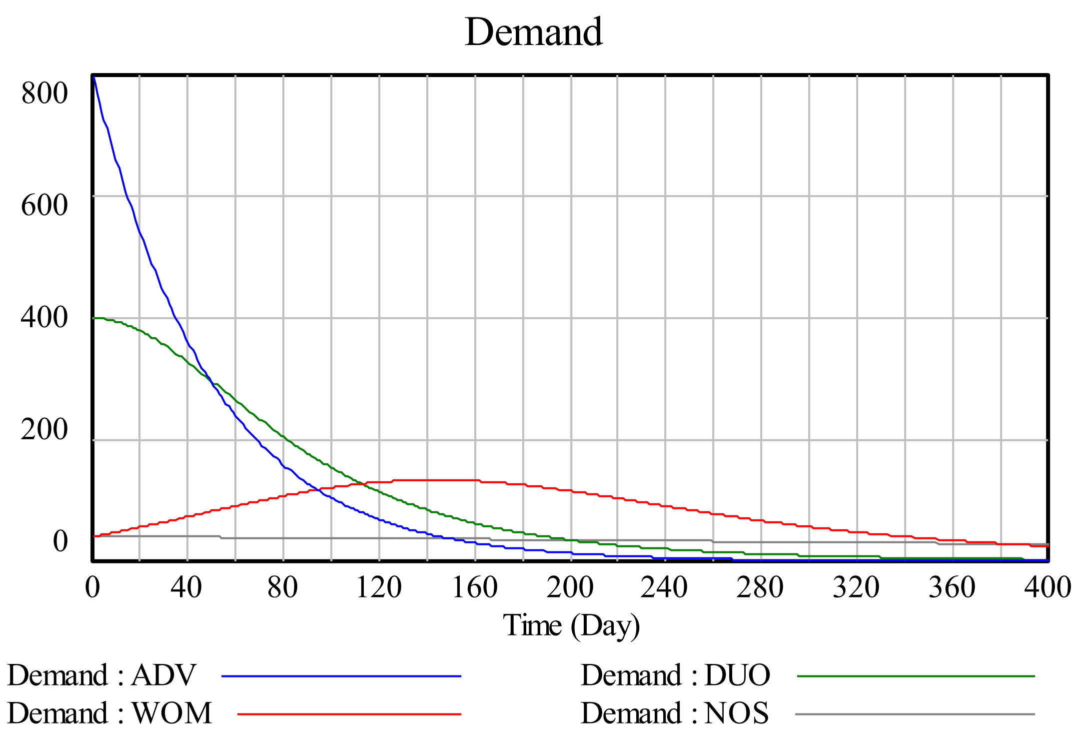
Table < 12-2> Setting parameters according to product strategy

strategy	Advertisement Effect Ratio	Word of Mouth Effect Ratio	Breakaway Ratio
InDV	0.02	0.001	0.01
WOM	0.001	0.02	0.01
DUO	0.01	0.01	0.01
NOS	0.001	0.001	0.01

When using the ADV strategy, the advertising effect is expected to be about 2%, and the oral effect is expected to be only 0.01%. In the case of the WOM strategy, the oral effect is increased to 0.02, but the advertising effect is almost not generated, so it is expected to be 0.001. DUO is similar to the strategy of taking two rabbits, with the intention of increasing the advertising effect while also increasing the oral effect. However, due to resource constraints, the advertising effect and the oral effect are expected to be 1% each. NOS is unstrategically unemployed, with both effects very low at 0.001. Breakaway Ratio of the four strategies: It was assumed that consumers who purchased once would opt out without repurchasing. If you withdraw, the oral effect no longer occurs.)

By entering the parameters for the four strategies and running the simulation, you can find the following demands.

<Figure 12-2> Demand according to four strategies



ADV strategy is a blue line. The line starts at 800 per day. Since there is almost no oral effect, only an advertising effect, it shows an exponential function pattern. Of the 40,000 people, 2% or 800 people will be in demand on the first day, and about 39,200 or 754 people, or 2%, will be in demand on the second day, which is missing from 40,000 to 800. Since the population decreases with each passing day, D emand shows a pattern of continuous decline even if the advertising effect is constant at 2%.

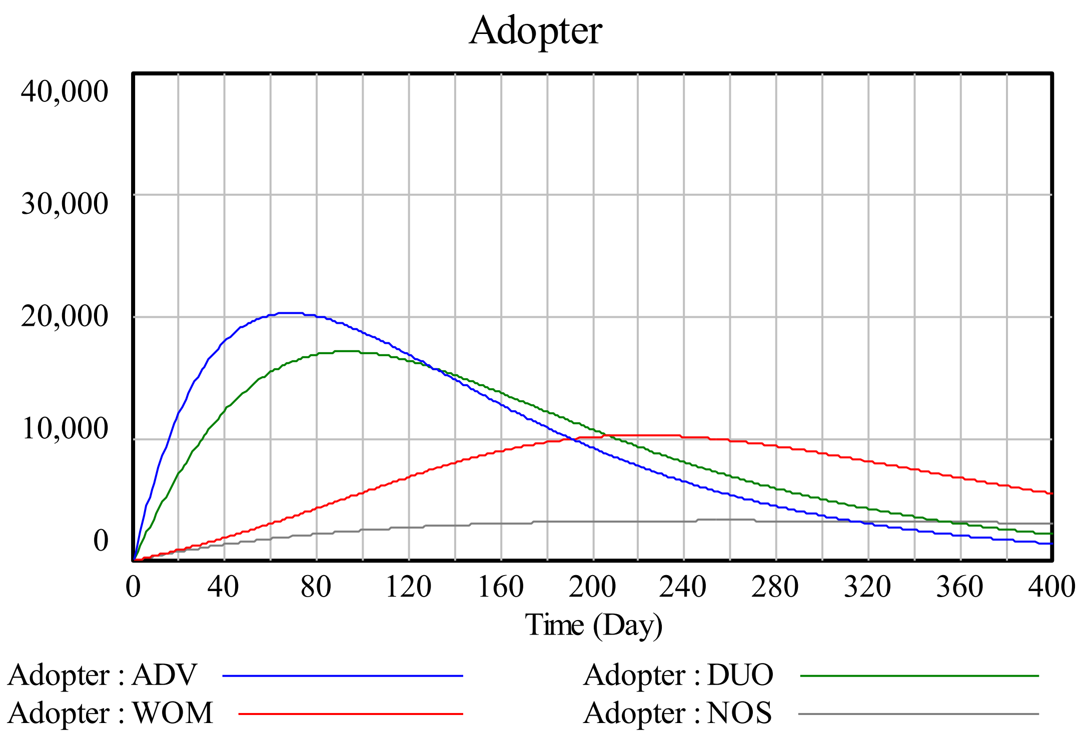
In the case of the WOM strategy, the demand is small when it starts from 0 days, but it increases exponentially due to the oral effect. After a certain value, it is dominated by negatibruff (advertising effect), and later the adopter is reduced by Breakaway and enters a period of decline. Although it is described as WOM, it is similar to the demand pattern according to the life cycle of a typical product. It is a pattern that leads to the introductory-growth-mature-decaying phase.

In the case of the DUO strategy, the line starts at 400. Since the advertising effect acts more initially than the oral effect, it shows a pattern that continues to decrease. However, it also has an oral effect, so the pattern of diminishing is different from ADV. It shows a form that is maintained longer.

Since the NOS strategy has not taken any action, demand remains constant without bending.

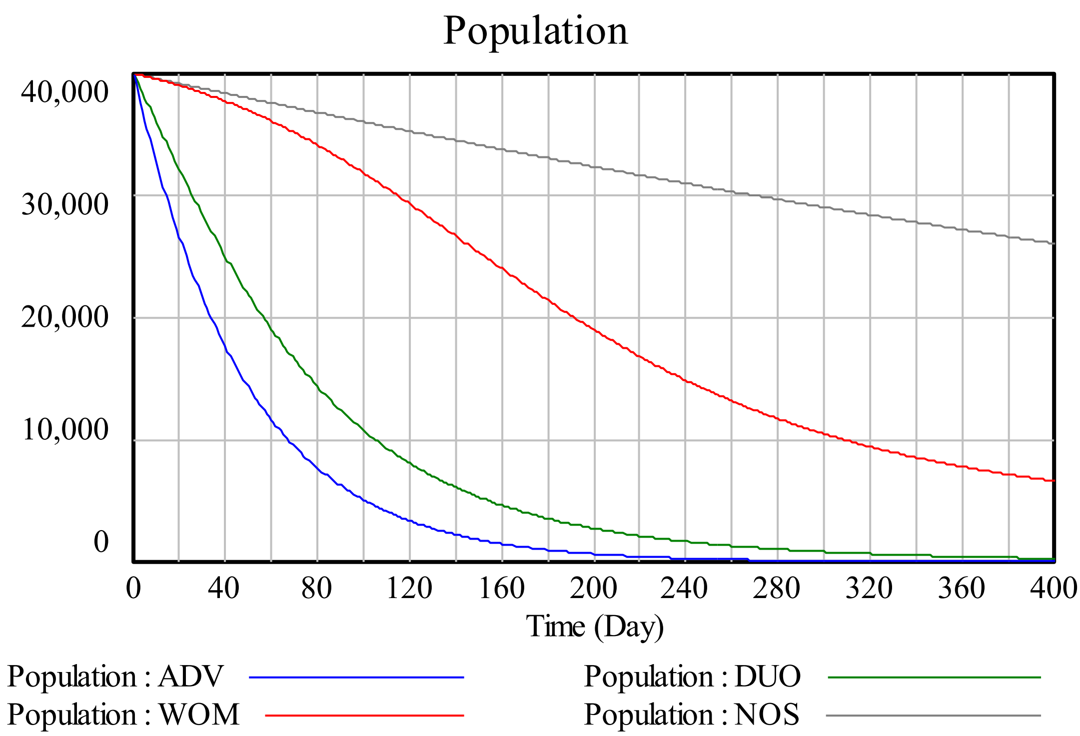
Adopter according to Demand appears as shown in the following figure.

<Figure 12-3> Adopter changes according to four strategies



The purchaser (adopter) differs depending on the strategy. In the case of the ADV strategy, it is a form of rapid adoption from the beginning and then quickly subsiding. Similar but lower peaks are the DUO strategy. The WOM strategy is in the form of reaching the top after 200 days and then softening again. In the case of the NOS strategy, the ascent is small, and it shows a pattern of reaching the top around 260 days and then gradually softening again.

<Figure 12-4> Population change according to four strategies

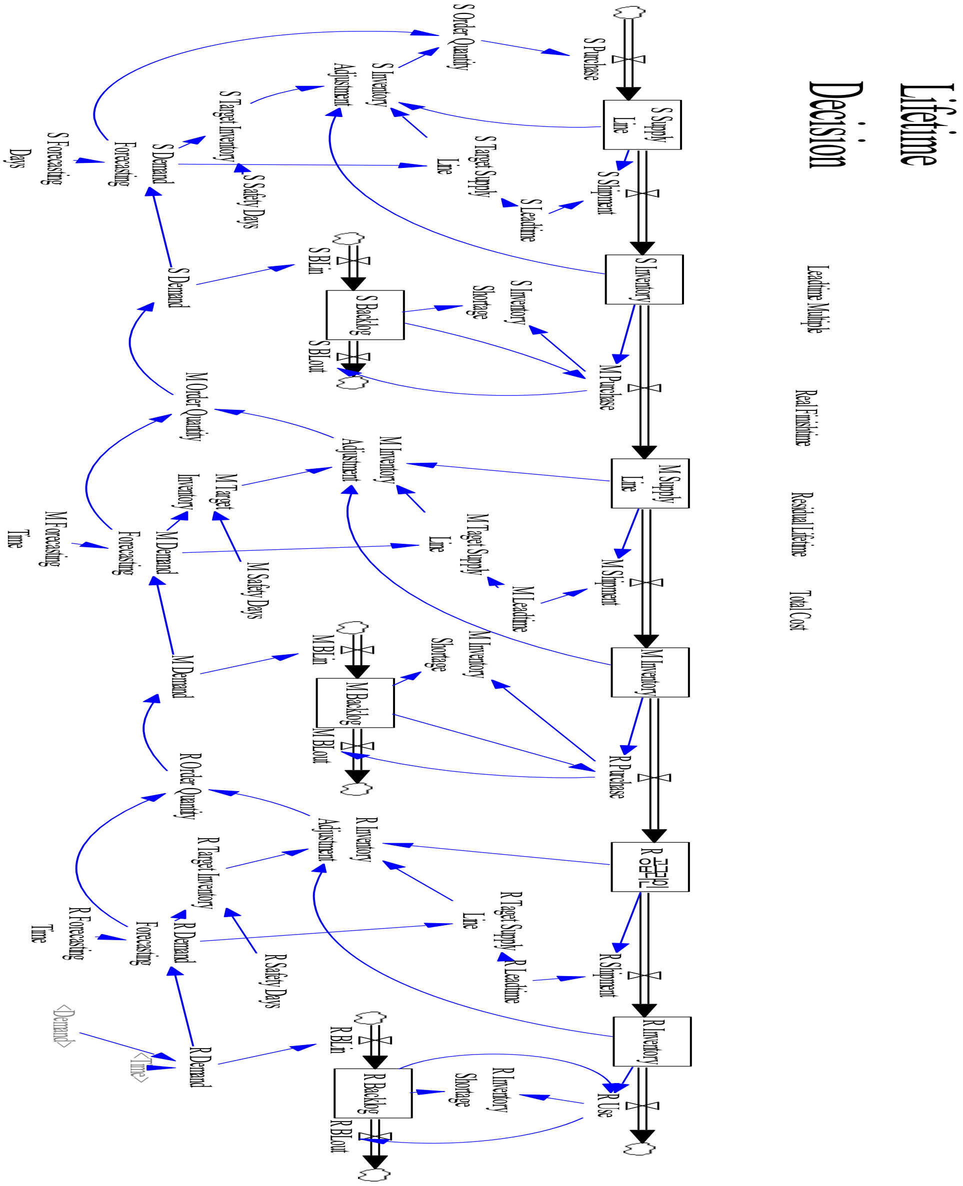


During the runtime for 400 days, only 11.21 were not in demand through the ADV strategy , with WOM remaining at 6,628, D UO at 277.64 and N OS at 26,088.

2) Supply chain performance according to product strategy

Then, on Bensim's next page, he created the following model: This model is frequently used in the previous chapters. It is based on the 3 57 model with a lead time of 3 days for R , 5 days for M, and 7 days for S. There are a few things that have changed. First of all, the demand (Demand) reflects the demand generated on the previous page. In other words, it reflected the form of demand according to the product strategy.

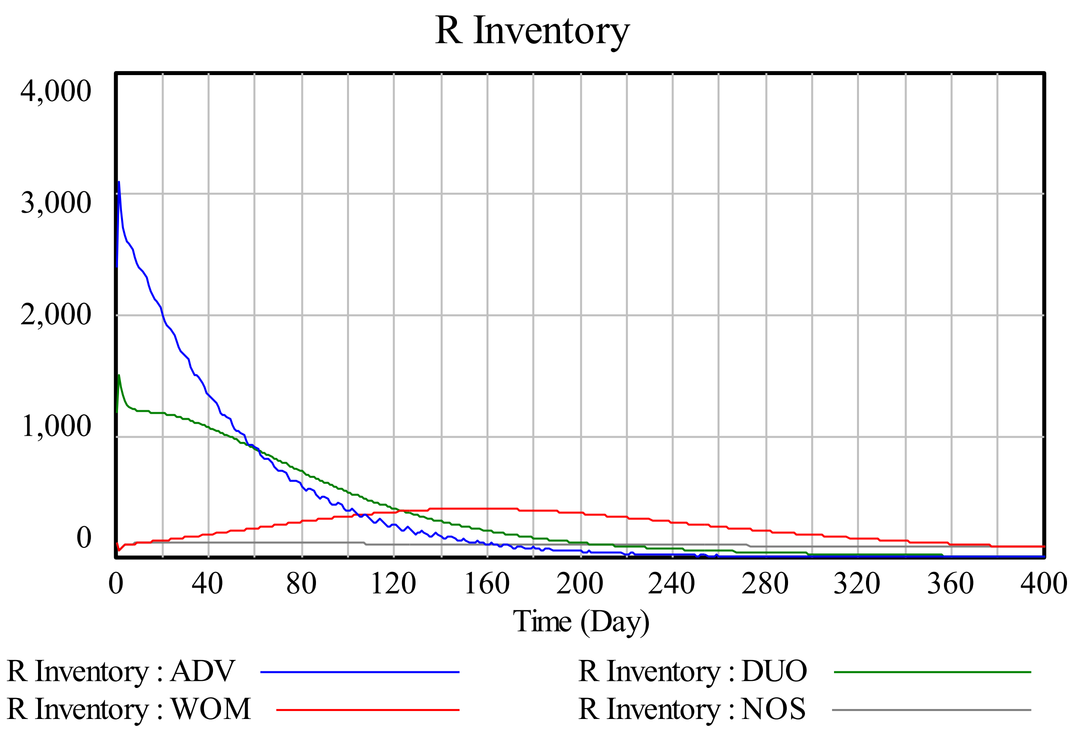
<Figure 12-5> Supply Chain Management Model



There are some new variables added to the top of the model, which we'll discuss later in the article.

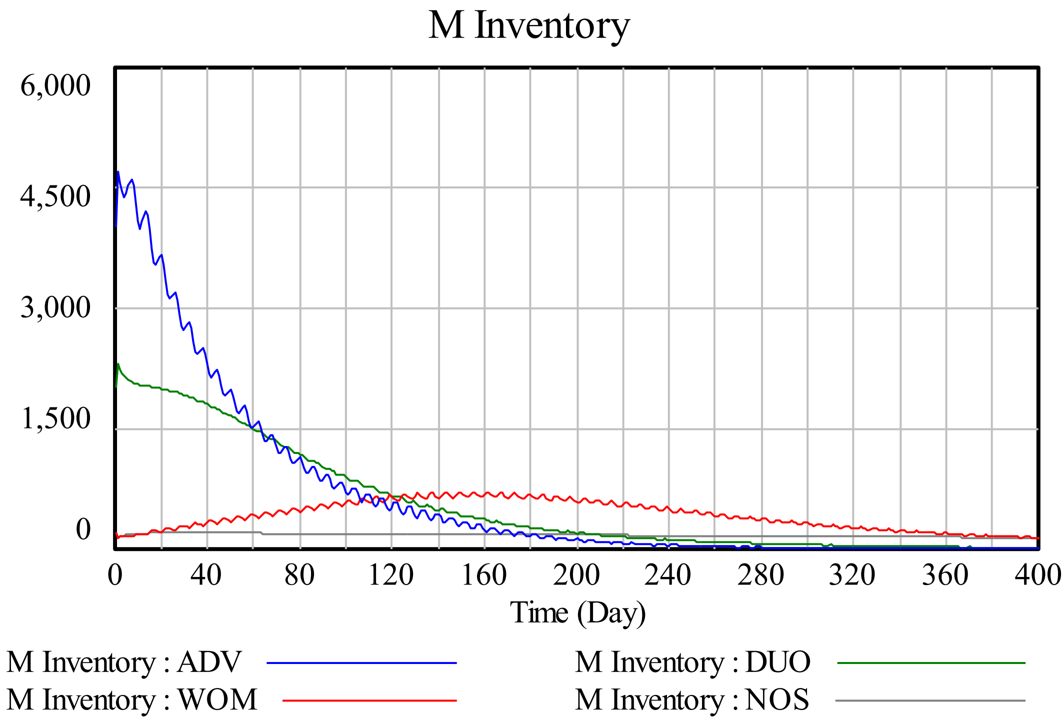
Lead times were 3, 5, and 7 days to run simulations. There is no management of target supply lines or target inventory levels.

<Figure 12-6> R Inventory according to Product Strategies in the 357 Supply Chain



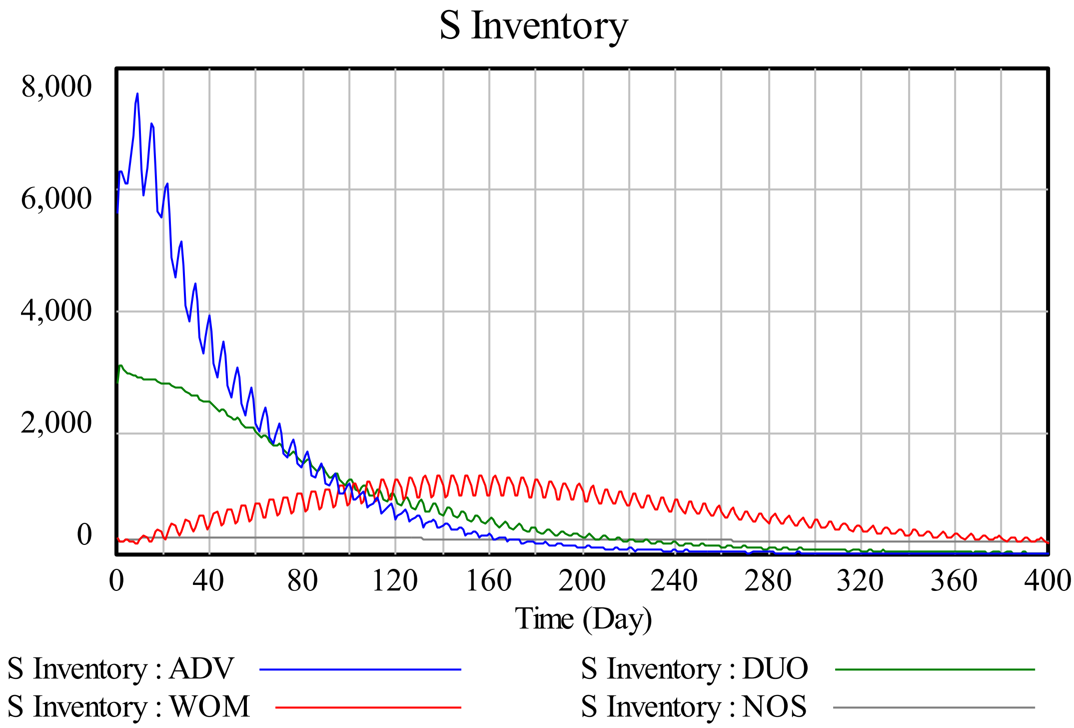
R Inventory appears similar to the demand pattern according to the product strategy. Some initial stocks have been lacking, resulting in backrock outbreaks, and the resulting sharp decline is partly manifested.

<Figure 12-7> M Inventory according to product strategy in the 357 supply chain



3The M Inventory of the 57 model also has a different pattern depending on the demand according to the product strategy. Only due to lead times, backlocks, etc., the jagged volatility increased. Especially in the case of ADV strategy products, this fluctuation is relatively large because it is necessary to hold a huge initial inventory.

<Figure 12-8> S Inventory according to product strategy in the 357 supply chain



S Inventory also shows the same pattern as other inventories, but with increased daily fluctuations.

357 Parameters related to profit were arbitrarily included in the model.

Table 12-3< > Randomly assigned variables and values for profit calculation

Variable life	value	Variable life	value	Variable life	value
S Supply Cost	2	M Supply Cost	4	R Supply Cost	6
S Sale Price	4	M Sale Price	6	R Sale Price	10
S Inventory Holding Cost	0.1	M Inventory Holding Cost	0.1	R Inventory Holding Cost	0.1
S Salvage Cost	1	M Salvage Cost	2	R Salvage Cost	3

In the supply chain, the supplier (S) buys the material for $2 and sells it to the producer M for $4, and the producer buys it for $4 and sells it to the retailer (R) for $6. Retailers sell to consumers for $10. All supply chain participants assumed that the cost of storing one unit of inventory per day was $0.1. Salvage cost on disposal of last remaining inventory was set at $1 for suppliers, $2 for producers, and $3 for retailers. This is half the purchase price. The current model sets the time to dispose of the remaining inventory to 400 days, so the actual disposal does not occur, so the salvage cost is not used.

For reference, the benefits of supply chain participants consist of the following equations.

S Profit = M Purchase*S Sale Price-S Inventory*S Inventory Holding Cost+S Discard*S Salvage Cost-S Purchase*S Supply Cost

M Profit = R Purchase*M Sale Price-M Inventory*M Inventory Holding Cost+M Discard*M Salvage Cost-M Purchase*M Supply Cost

R Profit = R Sale*R Sale Price-R Inventory*R Inventory Holding Cost+R Discard*R Salvage Cost-R Purchase*R Supply Cost

Total Profit = M Profit+R Profit+S Profit

Measuring the performance of a given supply chain structure is shown in the following table.

Table < 12-4> Performance of Product Strategies in Traditional Supply Chain Structures

strategy	S Profit	M Profit	R Profit	Total Profit
InDV	92.82	189.63	434.64	717.10
WOM	96.49	125.70	310.14	532.34
DUO	117.28	170.95	399.64	687.88
NOS	45.54	53.25	130.33	229.13

3) Supply chain management according to product strategy

So far, we've seen that the demand for products varies depending on the strategy, and what happens in a given supply chain. In this section, we will explore the optimal supply chain management method according to each product strategy. In supply chain management, the plan is limited to how each safety stock day is set. In other words, each Safe Day will be set to maximize the total profit.

(1) Supply chain management according to ADV strategy

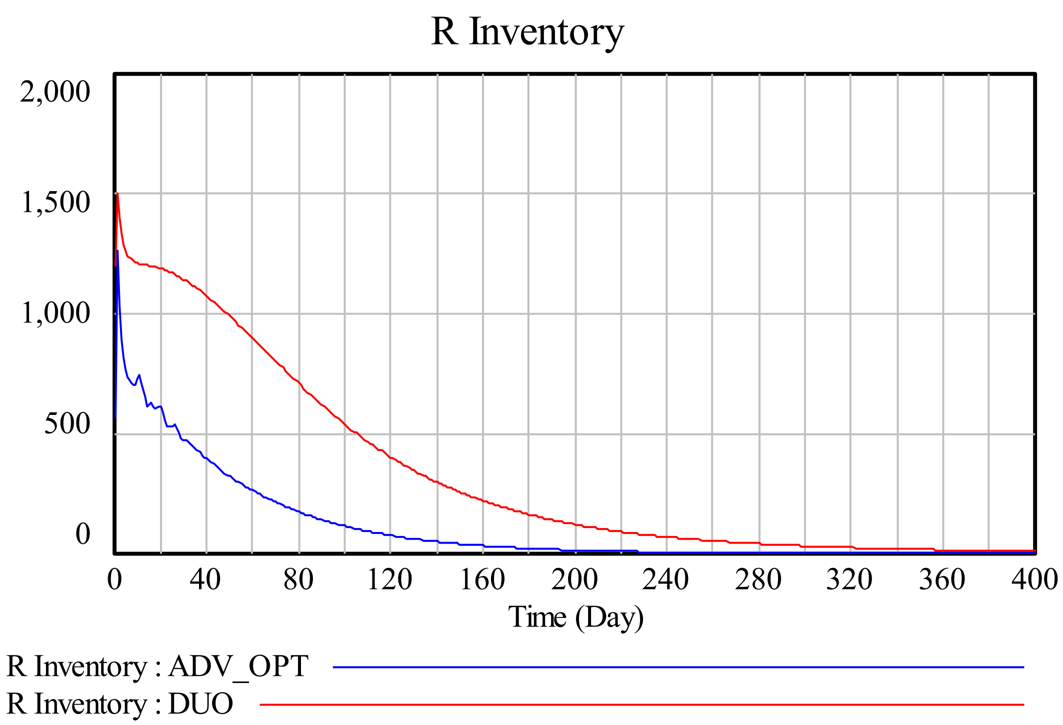
Demand is generated according to the ADV strategy. And the safe days of the supply chain must be reset to maximize profits. The number of safe days for each participant maximizing supply chain profits is as follows:

<12-5> Safety days that maximize supply chain benefits under ADV strategy

Safety days	Optimal parameter value
S Safety Days	0.0342668
M Safety Days	0.377739
R Safety Days	0.707465

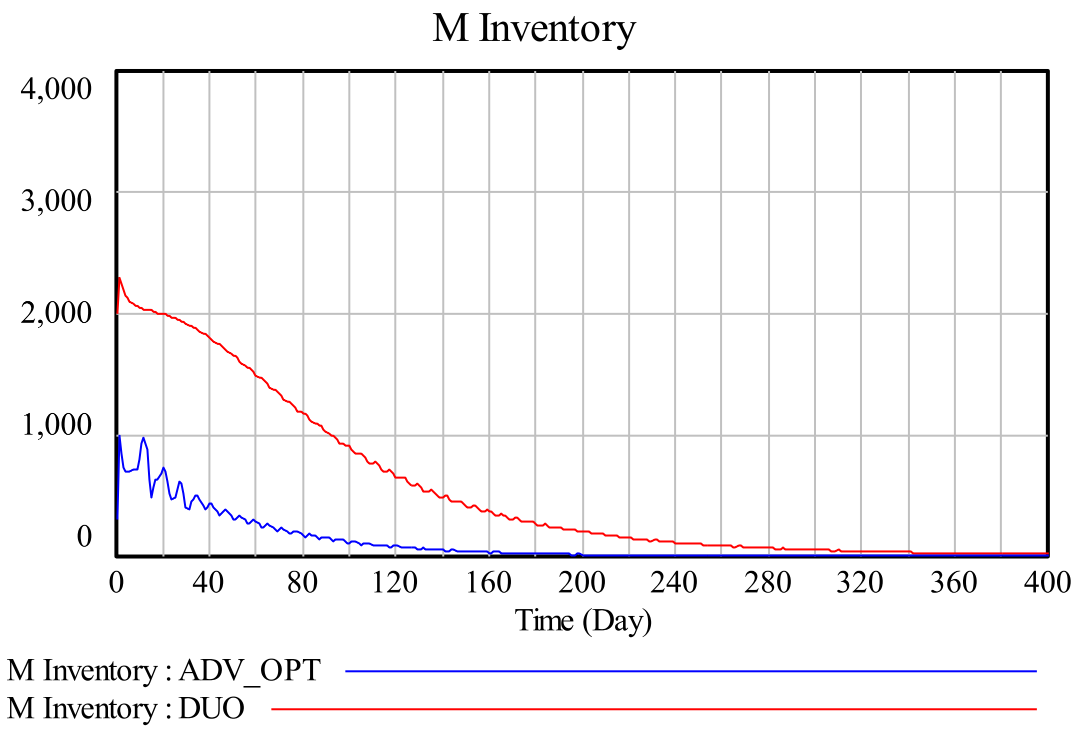
The average profit of the base model with lead times of 3, 5 and 7 days was 687.88, but after optimization there was a significant profit increase to 828.42.

<Figure 12-9> R Rethinking the Basic Model (ADV) and Optimal Model (ADV_OPT) in ADV Strategy



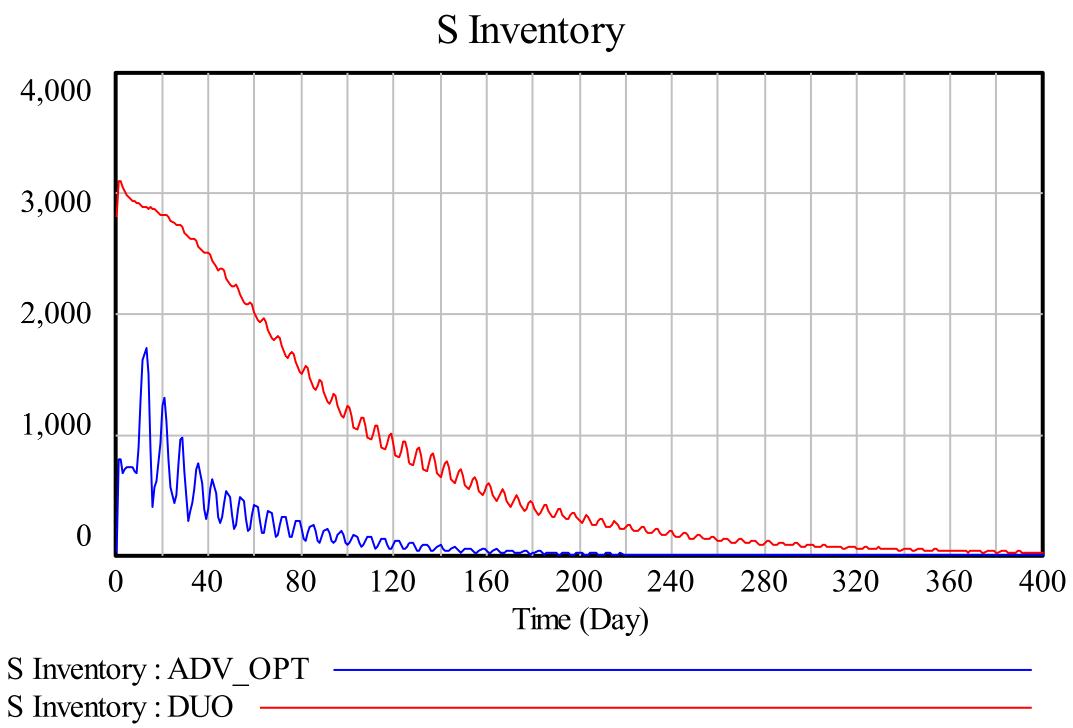
On the other hand, the average inventory of R Inventory of the ADV model was 332.09, which decreased by less than one-third to 109.61 after optimization.

<Figure 12-10> M inventory of basic model (ADV) and optimal model (ADV_OPT) in ADV strategy



The average inventory of M Inventory for the ADV model was 554.09, which was reduced by less than one-fifth to 112 after optimization. The decline was wider.

<Figure 12-11> Rethinking S of Basic Model (ADV) and Optimal Model (ADV_OPT) in ADV Strategy



The average inventory of S Inventory for the ADV model was 773.45, but after optimization it decreased by less than one-fifth to 134.63. The decline was slightly higher than M.

If you implement effective supply chain management while using a DV strategy, you can significantly reduce inventory and increase profits.

(2) Supply chain management according to WOM strategy

Demand is generated according to the WOM strategy. And the safe days of the supply chain must be reset to maximize profits. The number of safe days for each participant maximizing supply chain profits is as follows:

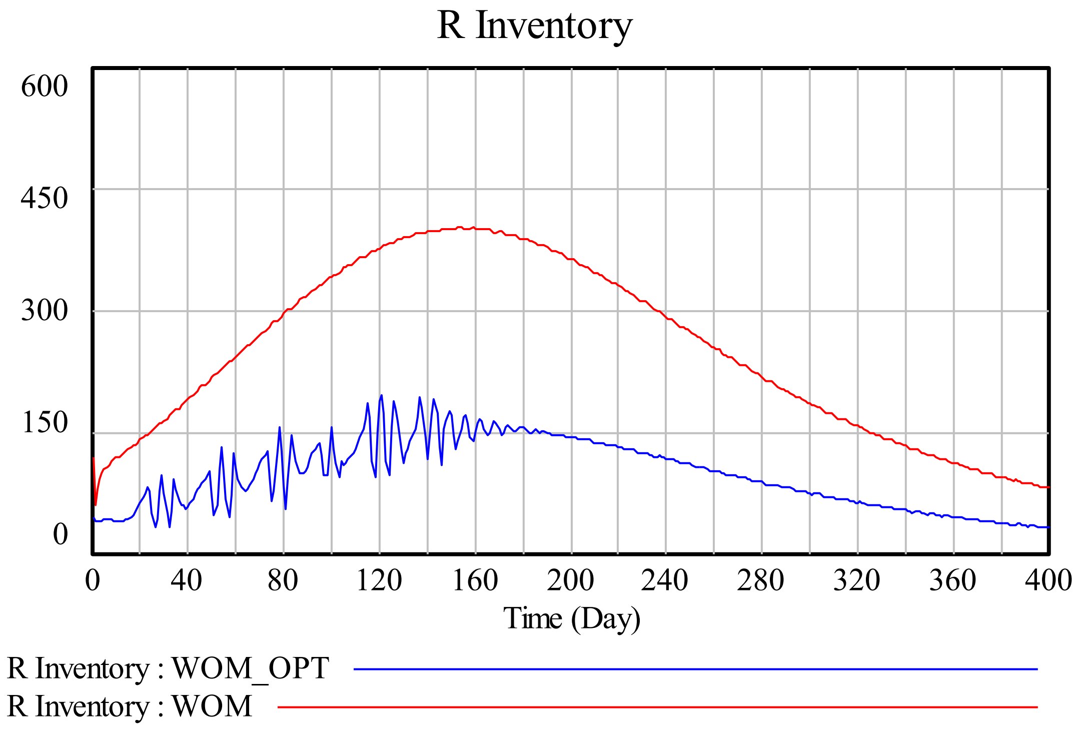
<12-6> Safety days that maximize supply chain benefits under WOM strategy

Safety days	Optimal parameter value
S Safety Days	1.46915

M Safety Days	1.06351
R Safety Days	1.15807

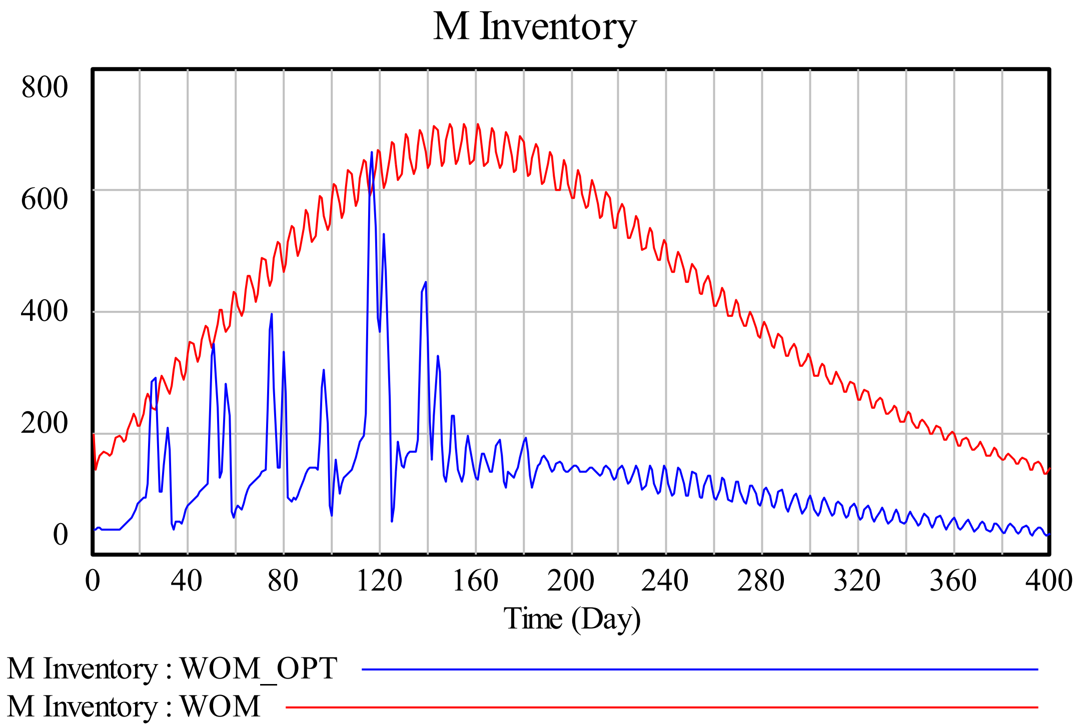
The average profit for the base model with lead times of 3, 5 and 7 days was 532.34, which after optimization was 631.65, representing an increase in profit of just below 20%.

<Figure 12-12> R Rethinking the Basic Model (WOM) and Optimal Model (WOM _OPT) in the WOM Strategy



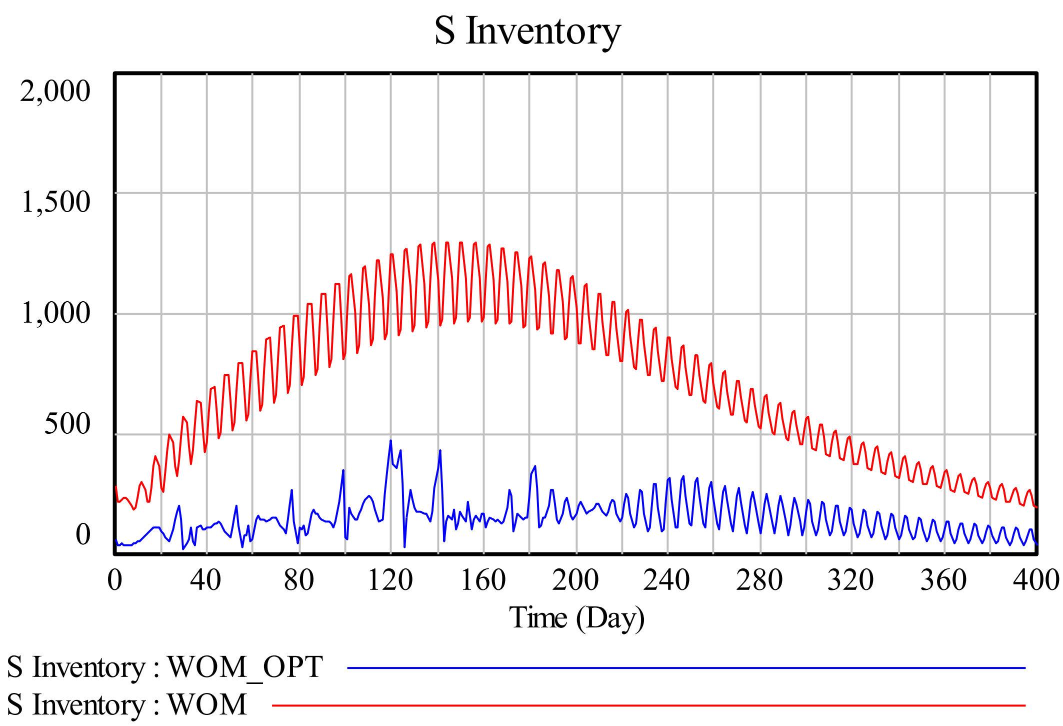
On the other hand, the average inventory of R Inventory of the WOM model was 250.56, but after optimization, it is 97.80, which has an inventory reduction effect of about 60%.

<Figure 12-13> M inventory of basic model (WOM) and optimal model (WOM _OPT) in WOM strategy



The average inventory of M Inventory of the WOM model was 421.88, but after optimization it was 124.39, indicating a decrease of about 70%. Within 100 days, in situations where demand increases, we can see a large deviation in inventory.

<Figure 12-14> S Rethinking the Basic Model (WOM) and Optimal Model (WOM _OPT) in WOM Strategy



The average inventory of S Inventory of the WOM model was 702.01, but after optimization, it was 151.30, a decrease of about 80%.

(3) Supply chain management according to the DUO strategy

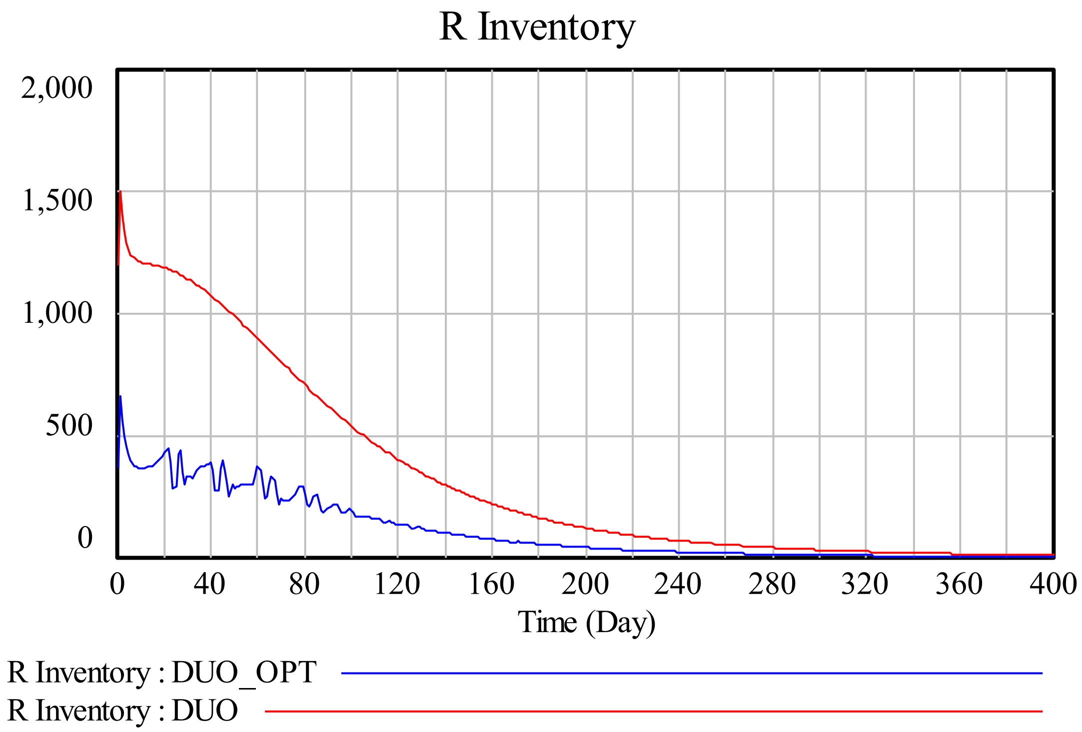
Demand is driven by the DUO strategy. And the safe days of the supply chain must be reset to maximize profits. The number of safe days for each participant maximizing supply chain profits is as follows:

<12-6> Safety days that maximize supply chain benefits under the DUO strategy

Safety days	Optimal parameter value
S Safety Days	0.363602
M Safety Days	0.819366
R Safety Days	0.969194

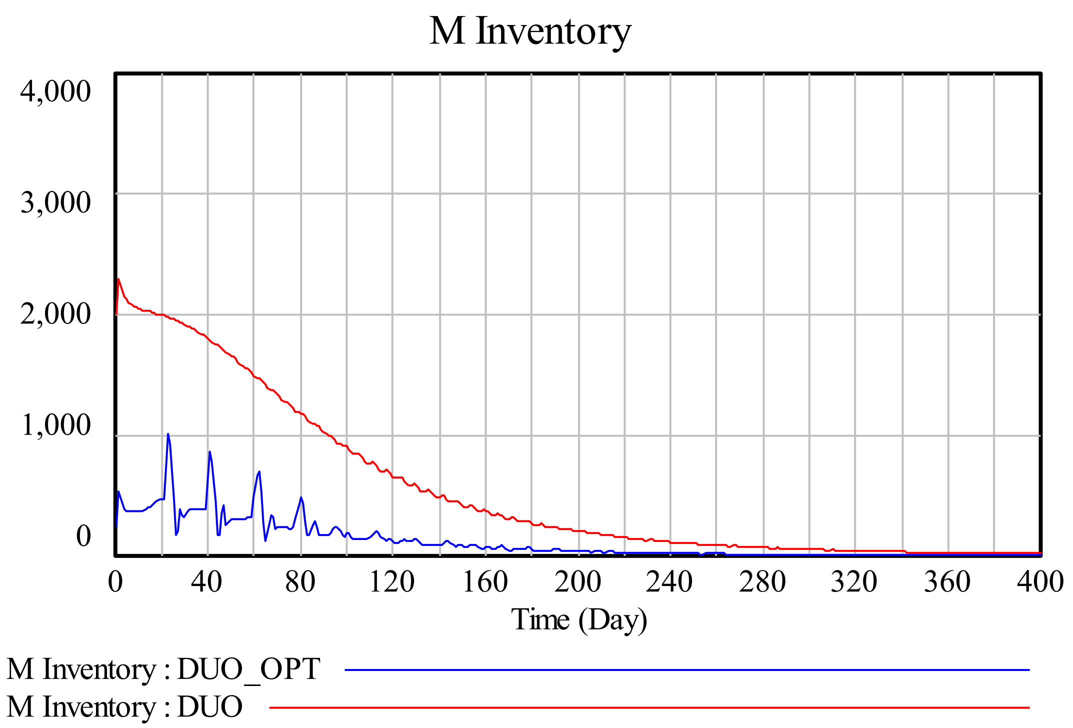
The average profit for the base model with lead times of 3, 5 and 7 days was 532.34, which after optimization was 631.65, representing an increase in profit of just below 20%.

<Figure 12-15> R inventory of the basic model (DUO) and optimal model (DUO _OPT) in the DUO strategy



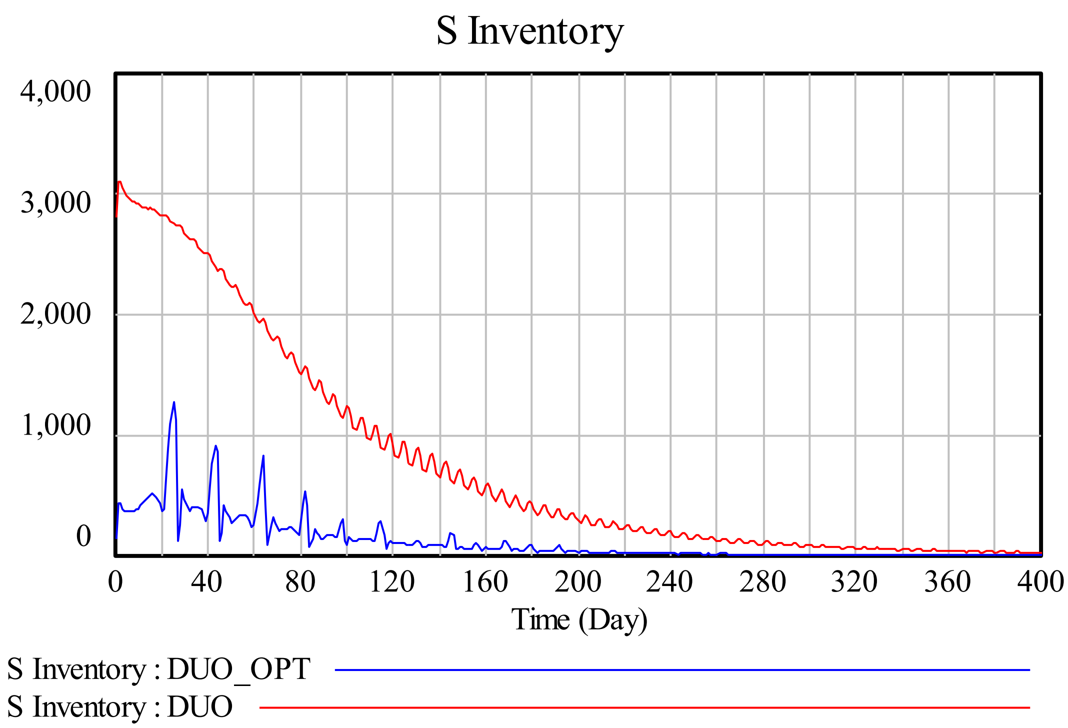
On the other hand, the average inventory of R Inventory of the DUO model was 332.09, which decreased by about 70% to 110.45 after optimization.

<Figure 12-16> M inventory of basic model (D UO) and optimal model (D UO _OPT) in DUO strategy



The average inventory of M Inventory of the DUO model was 554.05, but after optimization, it was 118.75, indicating a decrease of nearly 80%.

<Figure 12-17> S rethinking the basic model (DUO) and optimal model (DUO _OPT) in the DUO strategy



The average inventory of S Inventory of the DUO model was 773.45, but after optimization, it was 122.21, a decrease of more than 80%.

(4) Supply chain management according to NOS strategy

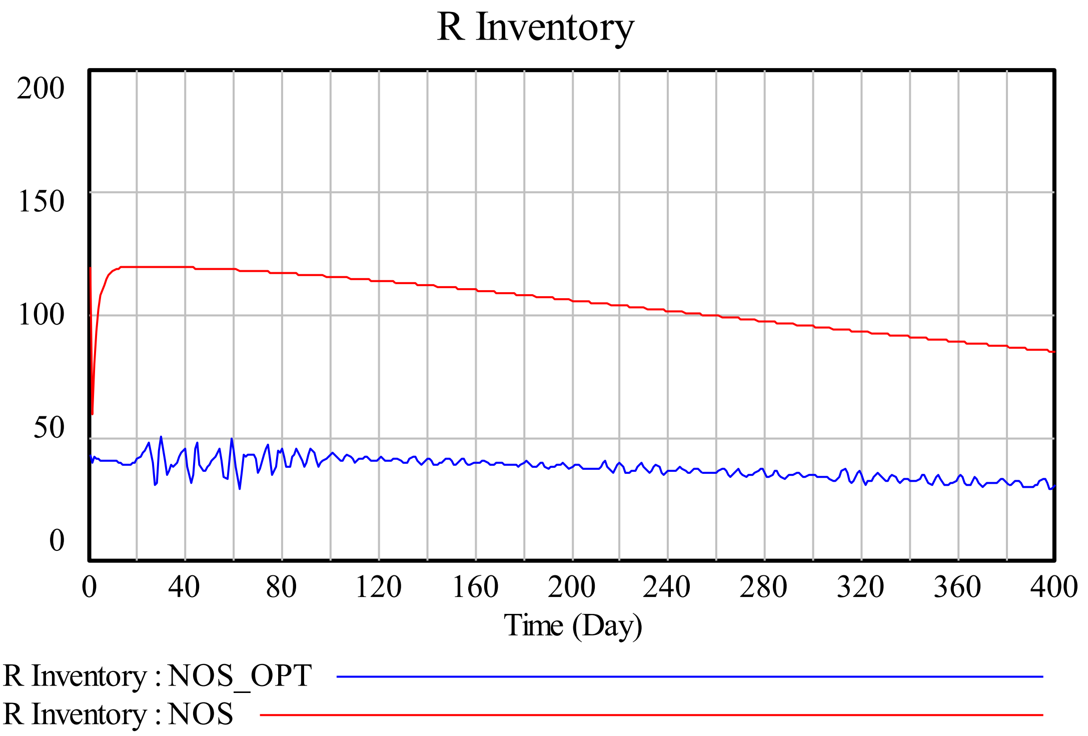
Demand is generated according to the NOS strategy. And the safe days of the supply chain must be reset to maximize profits. The number of safe days for each participant maximizing supply chain profits is as follows:

<12-7> Safety days that maximize supply chain profits under the NOS strategy

Safety days	Optimal parameter value
S Safety Days	1.09937
M Safety Days	1.15102
R Safety Days	1.06573

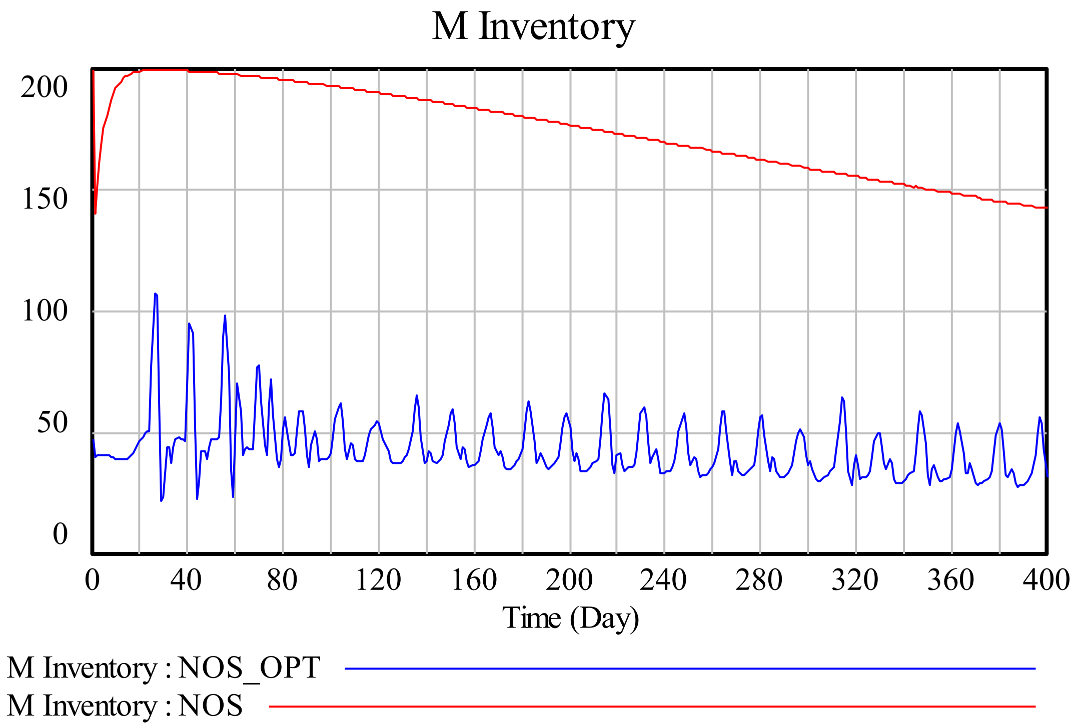
The average profit for the base model with lead times of 3, 5 and 7 days was 229.13, but after optimization, the profit increased slightly to 268.68.

<Figure 12-18> R inventory of basic model (N OS) and optimal model (N OS_OPT) in NOS strategy



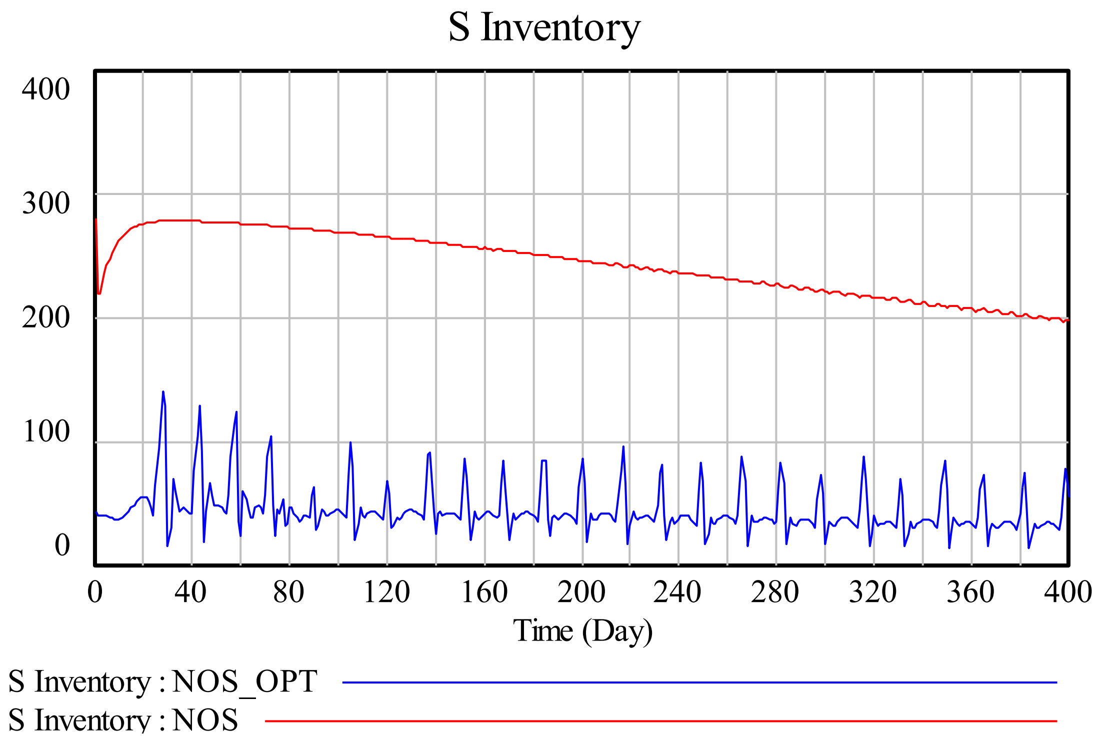
On the other hand, the average inventory of R Inventory for the NOS model was 104.79, but after optimization, it decreased by about 65% to 37.62.

<Figure 12-19> M inventory of basic model (N OS) and optimal model (N OS _OPT) in NOS strategy



The average inventory of M Inventory in the NOS model was 174.67, but after optimization, it was 43.19, indicating a inventory decrease of nearly 750%.

<Figure 12-20> S Rethinking the Basic Model (N OS) and Optimal Model (N OS _OPT) in the NOS Strategy

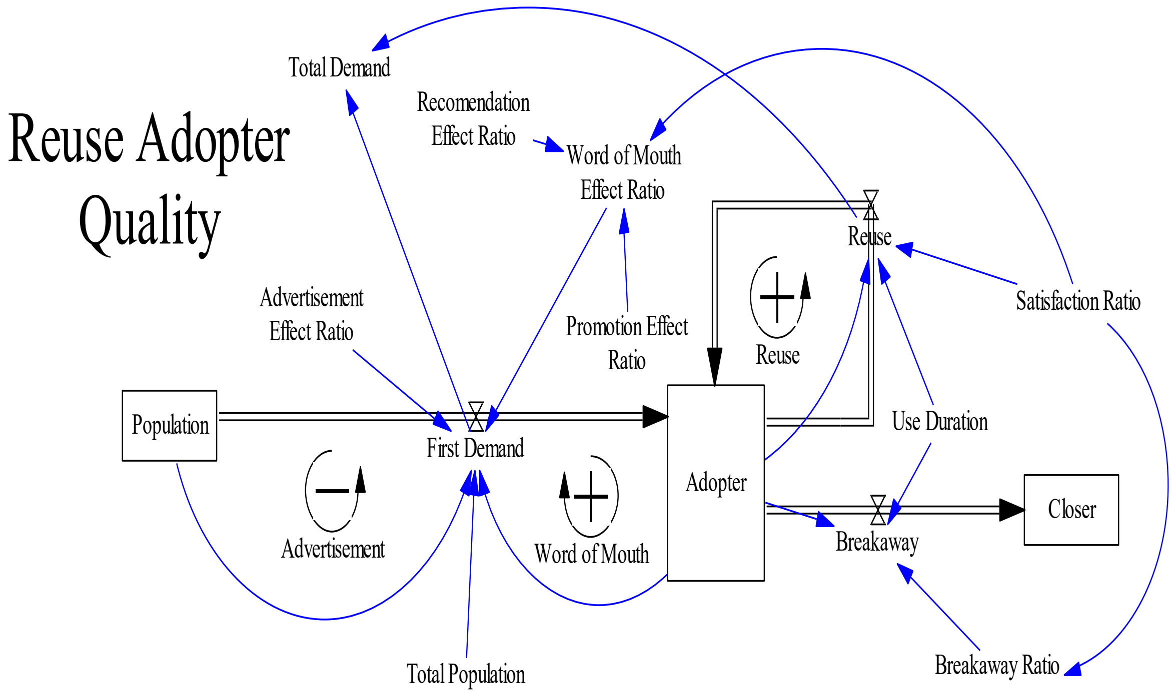


The average inventory of S Inventory of the NOS model was 243.59, but after optimization, it was 44.8, resulting in an inventory decrease of more than 80%.

4) Strategies for repurchasable products

In the product demand model in Figure 12-1< Figure 12-1> we look at the products that a person who has purchased once can buy again. Reflecting the repurchase process, we created a model like the following <Figure 12-21>.

<12-21> Product demand generation module when repurchasable



The relation for the added variables is as follows.

Adopter= INTEG (First Demand-Breakaway+Reuse-Reuse,1)

Satisfaction Ratio=0.9

Breakaway=Adopter*Breakaway Ratio/Use Duration

Recommendation Effect Ratio=0.1

Reuse=Adopter*Satisfaction Ratio/Use Duration

Promotion Effect Ratio=0.001

Word of Mouth Effect Ratio=Satisfaction Ratio*Recommendation Effect Ratio+Promotion Effect Ratio

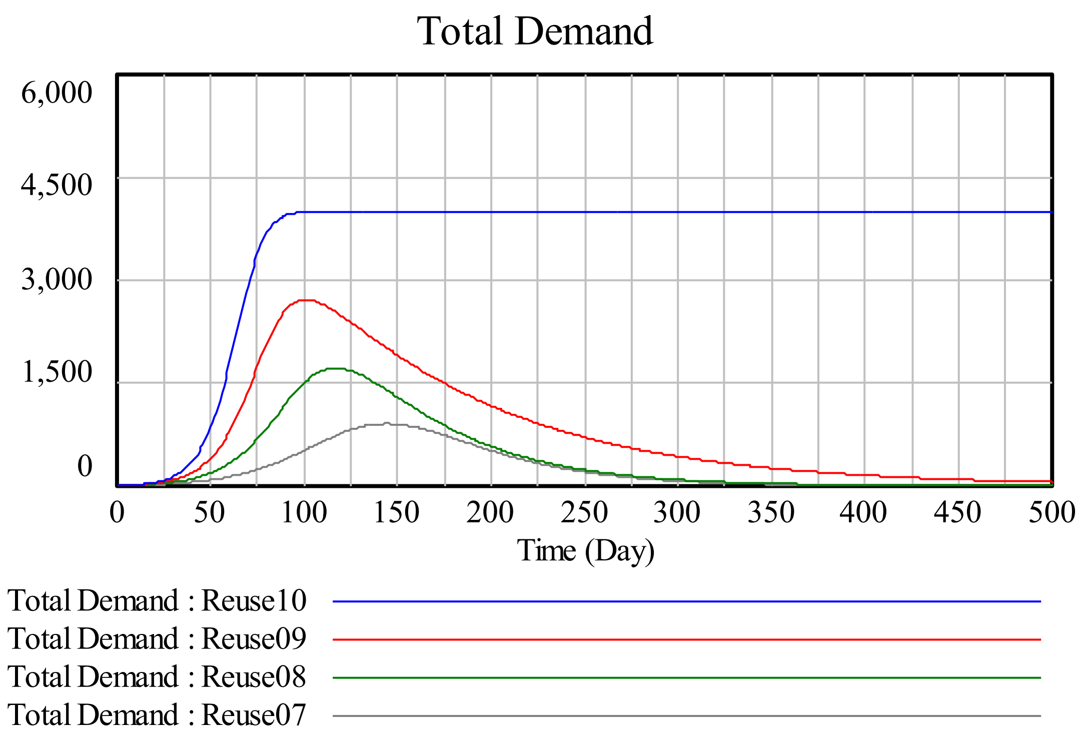
Total Demand=First Demand+Reuse

Use Duration=10

Adopters who have used it once will repurchase it depending on their satisfaction. The 1-Satisfaction Ratio is the percentage of consumers who no longer buy. It was assumed that satisfied customers would purchase again. It was assumed that this satisfaction would also affect the oral effect. It was judged that people with high satisfaction with using the product would strengthen the oral effect, so satisfaction was included in the oral effect ratio. Once purchased, it was assumed that the product would be used for 10 days.

In this model, customer churn determines overall supply chain performance. This is because the churn rate determines how much the market will continue to shrink. Looking at the total demand (Total Demand = Demand + Reuse) according to satisfaction , it is shown in the following figure. At this time, it was assumed that the advertising effect was 0.0001 and the promotion effect was 0.001.

<Figure 12-22> Changes in Total Demand by Satisfaction Ratio



When the satisfaction rate is 100%, customer churn does not occur. Therefore, aggregate demand does not decrease, as shown in the blue line in <Figure 12-22>. We can see that 4,000 pieces are in demand. The next line is 90% satisfied. At this time, the maximum demand is around 2,719, and the average daily demand is 786.89. The bottom line represents 80% and the bottom line represents 70%. In 70% of cases, the average daily demand is only 234.99.

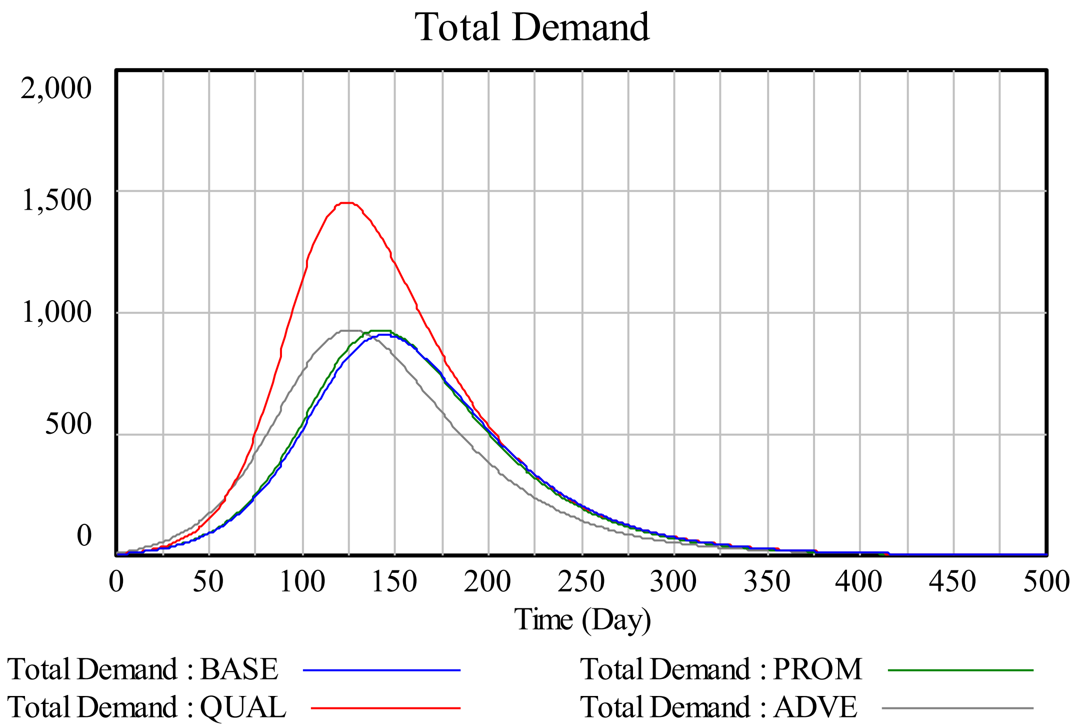
Adjust the parameters to distinguish strategies for each product. According to the combination of parameters, the product strategy was arbitrarily named as shown in the following table.

Table < 12-8> Parameter Combinations by Strategy

	Advertisement Effect Ratio	Promotion Effect Ratio	Satisfaction Ratio
Basic Model (BASE)	0.0001	0.001	0.7
Ad Expansion Strategy (ADVE)	0.0002	0.001	0.7
Promotional Expansion Strategy (PROM)	0.0001	0.002	0.7
Quality Improvement Strategy (QUAL)	0.0001	0.001	0.77

Expanding from 0.0001 to 0.0002 in the ad expansion strategy is a 100% performance improvement, and in the promotion expansion strategy, it is a 100% increase from 0.001 to 0.002. On the other hand, the quality improvement strategy hopes that the expansion from 0.7 to 0.75 will have an improvement effect of 10%. These strategies come with a cost. How much cost-performance improvement can be achieved varies from industry to industry. Here, it is assumed that the improvement effect in each strategy is different. This does not mean that the costs associated with these strategies are the same.

<Figure 12-23> Total Demand Change by Product Strategy



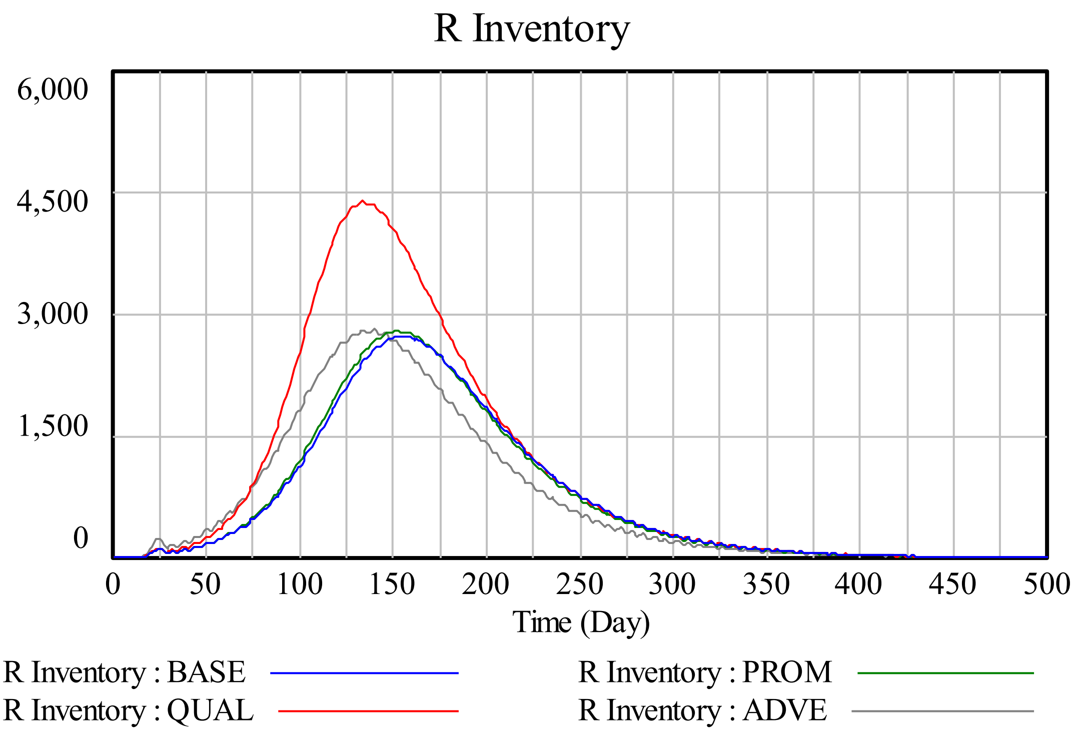
For BASE, it is a blue line. Compared to BASE, the promotional expansion strategy (PROM) is marginal, but it has the effect of slightly accelerating the growth of demand and peak demand. In the case of ADVE, it increases the timing and peak of demand faster and slightly more than the P ROM. Of course, the effect of Q UAL is very significant.

For the total duration of the simulation of 500 days, the average daily demand is BASE = 234.99, PROM = 236.26, ADVE = 236.96. Doubling the advertising effect and doubling the promotional effect involves costs. Depending on the cost, the increased demand through ADVE and PROM strategies averages only 1.27 and 1.98 units per day.

In the case of gross profit (Total Profit=S Profit+M Profit+ R Profit), the daily average is BASE=1,481, PROM=1,489, ADVE=1,485, QUAL=2,112. What's unusual is that gross profit has a slightly larger increase in PROM than ADVE. This is because in the case of ADVE, there is a high probability of initial inventory failure. This is because the advertising effect has increased, but the possibility of not securing sufficient inventory increases. However, we cannot conclude that this is a significant difference.

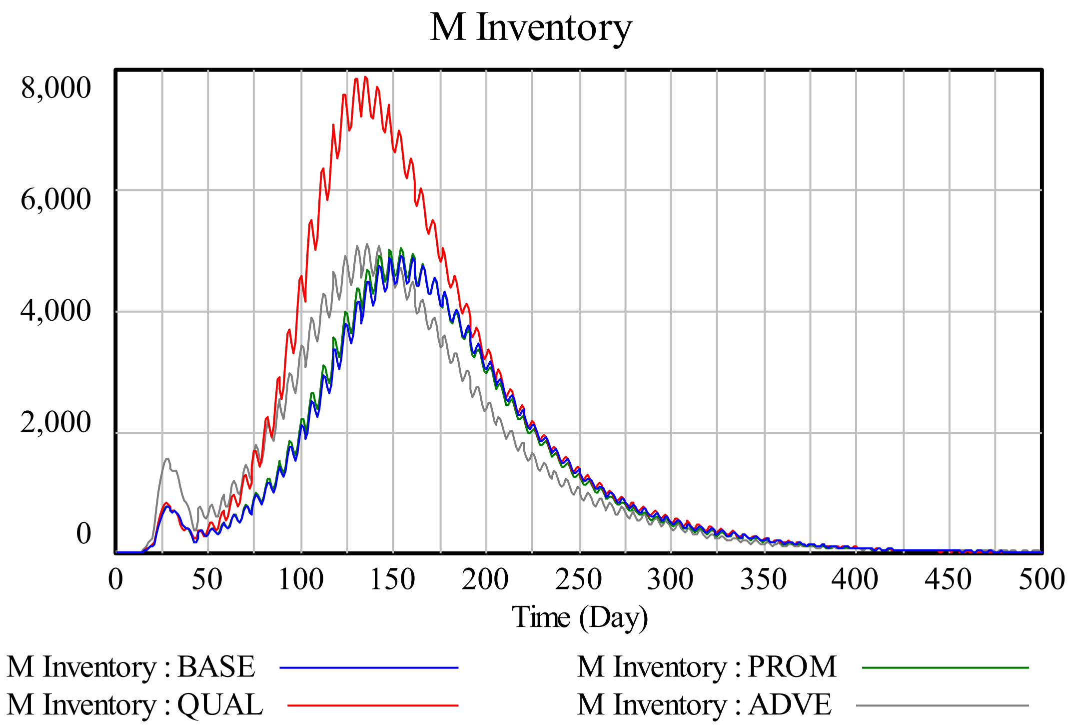
It doesn't make much sense for demand to grow quickly and then soften quickly. Rather, you can get up slowly and then slowly. In the case of repurchases, in the case of advertising expansion strategies or promotional expansion strategies, they only accelerate the time of occurrence of demand, but do not significantly increase the demand itself. If the demand will occur someday, it means that it can occur slowly. On the other hand, the quality expansion factor is different. By increasing royalties on the market or the product, repurchases continue to occur , which has the effect of growing and maintaining demand itself.

<12-24> R Inventory by Product Strategy (R Inventory)



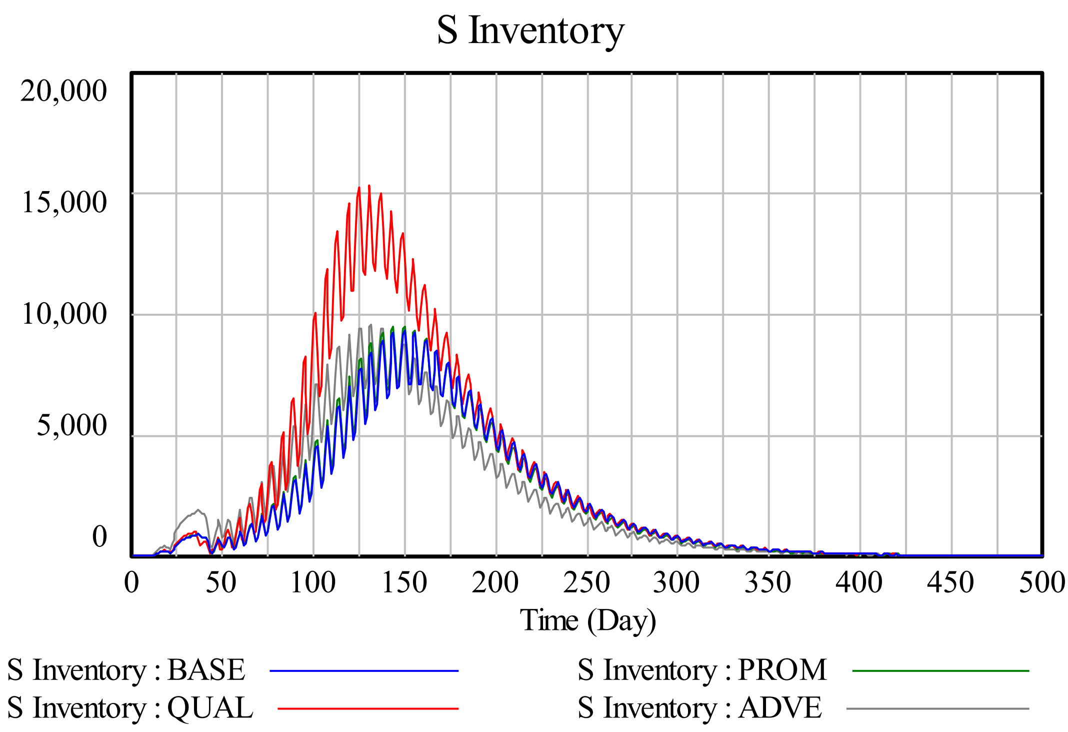
R inventories are almost similar to demand patterns. It is noticeable that the demand occurred 10 days ago, but there was an outstanding order, which led to a slight increase in inventory.

<12-24> M Inventory by Product Strategy (M Inventory)



In the case of M stock, the bumpiness appears to be larger than the R stock. And the R inventory initially bounced off some of the shortfall adjustments, which is still linked to M and amplified.

<12-24> S Inventory by Product Strategy



Between 0 and 50 days, an inventory adjustment due to lack of inventory seems to have occurred. The rest of the period shows that the demand pattern remains the same as the inventory pattern . Compared to demand, inventory is expressed as bumpy because it is a system that receives and uses a certain amount of supply.

The optimal inventory amount for each of these products can be calculated again, and the exit strategy can be built separately.

1Chapter 3

Exit strategies by product

Exit Strategy in the Supply Chain

In Chapter 12, we saw that demand varies depending on product strategy, and supply chain management must change accordingly. Chapter 13 uses the same model and looks at exit strategies.

Each product has a life cycle, and each product has a different margin structure. In general, for high-margin products, the word of mouth effect is chosen a lot, and for low-margin products, advertising is used a lot. This is not always the case. If you use a lot of advertising, there is a good chance that the product will quickly enter the maturity stage because many products are sold early on and demand tends to be concentrated at the beginning. If we enter the mature and declining period quickly, we will naturally have to exit the market faster.

Maintaining inventory comes at a high cost. In particular, it is necessary to purchase raw materials or buy goods in advance at the cost of items, which increases the financial burden. Therefore, the cost of maintaining inventory increases the likelihood that the exit period will be determined. Even though the cost of maintaining inventory is high, if it is not removed, profits will inevitably decrease.

This chapter presents the process of determining the optimal exit period for only two products: products with high advertising effect (ADV products in Chapter 12) and products with high oral effect (WOM in Chapter 12).

1) Exit strategy of ADV products

The 357 supply chain model discussed in Chapter 1 is combined with the demand generation module (ADV) for large advertising effects. Then modify the supply chain module by including the following variables and relations:

Create variables called Real Finishtime and Leadtime Multiple and enter any constant.

and

Residual Lifetime = Real Finishing-Time

Each supply chain includes a flow variable called a Discard in the inventory portion. Real is modeled as receiving and disposing of a certain Salvage Cost the day after the finishtime.

S Order Quantity = IF THEN ELSE(Residual Lifetime<=(S Leadtime+M Leadtime+R Leadtime)*Leadtime Multiple, 0, MAX(0, S Inventory Adjustment+S Demand Forecasting))

S Discard= IF THEN ELSE(Time>=Real Finishtime+1, S Inventory, 0)

M Discard = IF THEN ELSE(Time>=Real Finishtime+1, M Inventory, 0)

R Discard = IF THEN ELSE(Time>=Real Finishtime+1, R Inventory, 0)

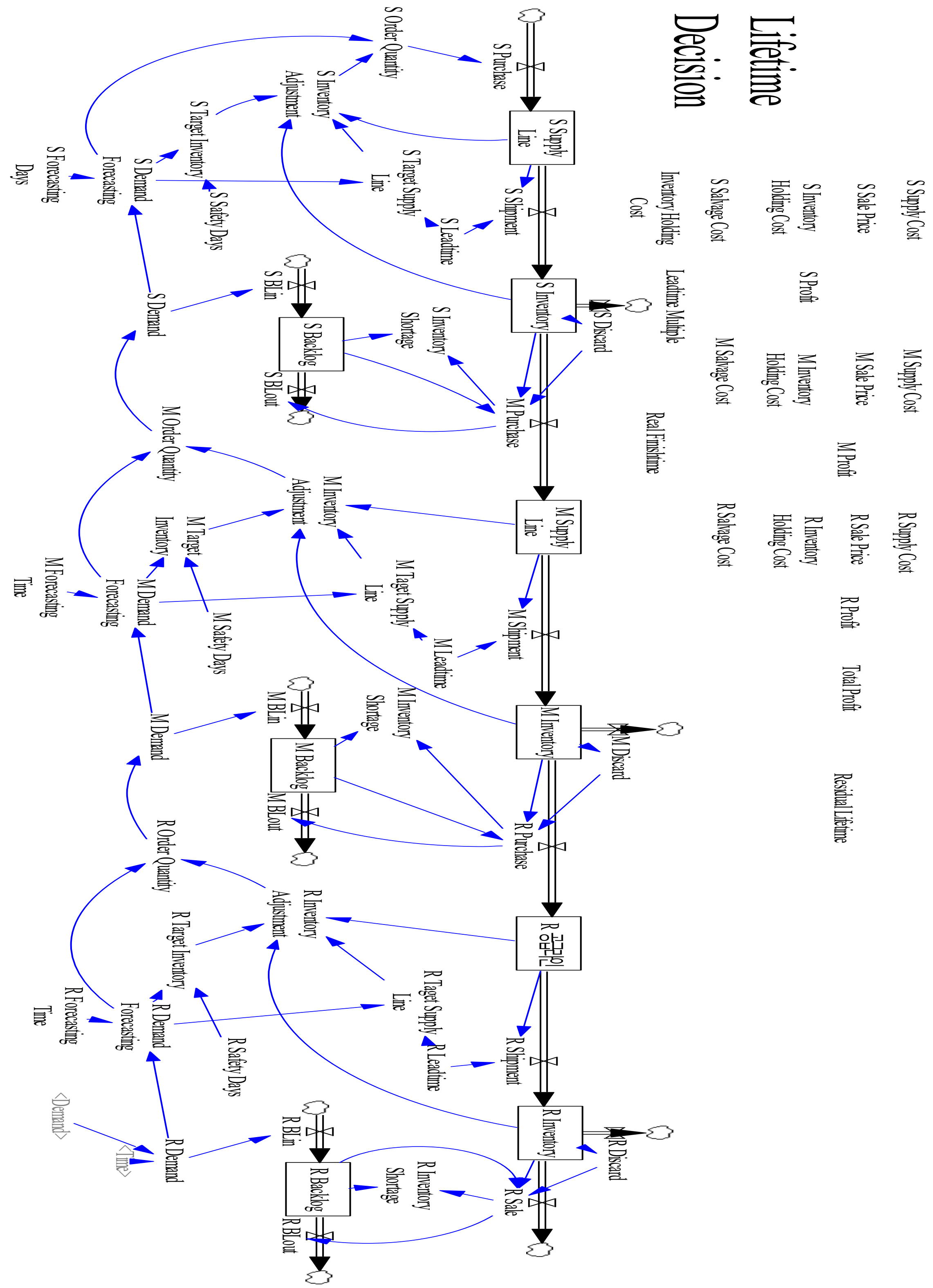
At this time, D iscard should be reflected in the outflow variables M Purchase, R Purchase, and R Sale in each inventory. Otherwise, the inventory will be doubled out, and the inventory will be negative.

M Purchase = MIN(S Backlog, S Inventory-S Discard)

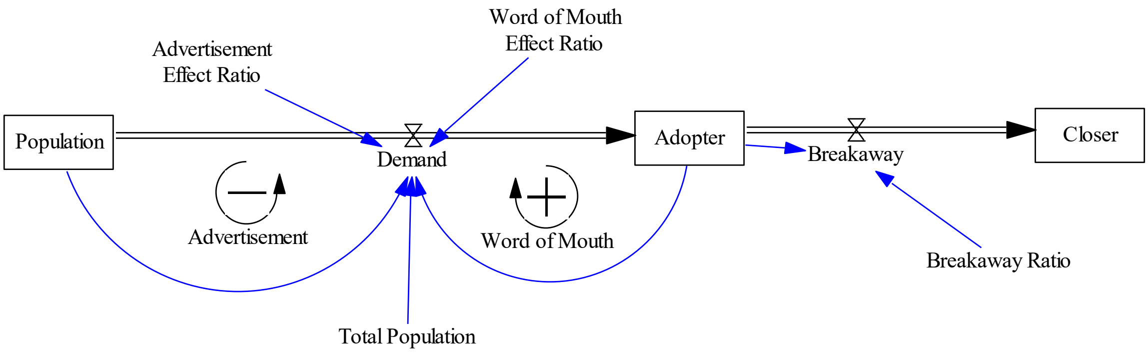
R Purchase = MIN(M Inventory-M Discard, M Backlog)

R Sale = MIN(R Backlog, R Inventory-R Discard)

<Figure 13-1> Supply Chain Segments of Advertising Products (ADVs)



<Figure 13-2> Product demand generation of advertising products (ADV)



The constant values and formulas used in the model are as follows.

Adopter= INTEG (Demand-Breakaway,1)

Advertisement Effect Ratio=0.02

Breakaway Ratio=0.01

Breakaway=Adopter*Breakaway Ratio

Closer= INTEG (Breakaway,0)

Demand=MAX(0, Population*Advertisement Effect Ratio+Adopter*Word of Mouth Effect Ratio*Population/Total Population)

Inventory Holding Cost=0.1

Leadtime Multiple=0

M Backlog= INTEG (M BLin-M BLout,100)

M BLin=M Demand

M BLout=R Purchase

M Demand Forecasting=SMOOTH(M Demand, M Forecasting Time)

M Demand=R Order Quantity

M Discard=IF THEN ELSE(Time>=Real Finishtime+1, M Inventory, 0)

M Forecasting Time=5

M Inventory Adjustment=M Taget Supply Line-M Supply Line+M Target Inventory-M Inventory

M Inventory Holding Cost=Inventory Holding Cost

M Inventory Shortage=MAX(0, M Backlog-R Purchase)

M Inventory= INTEG (M Shipment-R Purchase-M Discard,M Target Inventory)

M Leadtime=5

M Order Quantity=MAX(0, M Demand Forecasting+M Inventory Adjustment)

M Profit=R Purchase*M Sale Price-M Inventory*M Inventory Holding Cost+M Discard*M Salvage Cost -M Purchase*M Supply Cost

M Purchase=MIN(S Backlog, S Inventory-S Discard)

M Safety Days= 5

M Sale Price=6

M Salvage Cost=M Supply Cost*0.5

M Shipment=M Supply Line/M Leadtime

M Supply Cost= S Sale Price

M Supply Line= INTEG (M Purchase-M Shipment,M Taget Supply Line)

M Taget Supply Line=M Demand Forecasting* M Leadtime

M Target Inventory=M Demand Forecasting*M Safety Days

Population= INTEG (-Demand,Total Population-Adopter-Closer)

R Backlog= INTEG (R BLin-R BLout,100)

R BLin= R Demand

R BLout=R Sale

R Demand Forecasting= SMOOTH(R Demand, R Forecasting Time)

R Demand=IF THEN ELSE(Time>=Real Finishtime, 0, Demand)

R Discard=IF THEN ELSE(Time>=Real Finishtime+1, R Inventory, 0)

R Forecasting Time=3

R Inventory Adjustment=R Target Inventory-R Inventory+R Taget Supply Line-R Supply Line

R Inventory Holding Cost=Inventory Holding Cost

R Inventory Shortage=MAX(0, R Backlog-R Sale)

R Inventory= INTEG (R Shipment-R Sale-R Discard,R Target Inventory)

R Leadtime=3

R Order Quantity=MAX(0, MAX(0, R Demand Forecasting+R Inventory Adjustment))

R Profit=R Sale*R Sale Price-R Inventory*R Inventory Holding Cost+R Discard*R Salvage Cost-R Purchase*R Supply Cost

R Purchase=MIN(M Inventory-M Discard, M Backlog)

R Safety Days=3

R Sale Price=10

R Sale= MIN(R Backlog, R Inventory-R Discard)

R Salvage Cost=R Supply Cost*0.5

R Shipment=R Supply Line/R Leadtime

R Supply Cost=M Sale Price

R Supply Line= INTEG (R Purchase-R Shipment,R Taget Supply Line)

R Taget Supply Line=R Demand Forecasting*R Leadtime

R Target Inventory=R Demand Forecasting*R Safety Days

Real Finishtime=400

Residual Lifetime=Real Finishtime-Time

S Backlog= INTEG (S BLin-S BLout,100)

S BLin= S Demand

S BLout=M Purchase

S Demand Forecasting= SMOOTH(S Demand, S Forecasting Days)

S Demand=M Order Quantity

S Discard=IF THEN ELSE(Time>=Real Finishtime+1, S Inventory, 0)

S Forecasting Days=7

S Inventory Adjustment=S Target Inventory-S Inventory+S Target Supply Line-S Supply Line

S Inventory Holding Cost=Inventory Holding Cost

S Inventory Shortage=MAX(0, S Backlog-M Purchase)

S Inventory= INTEG (S Shipment-M Purchase-S Discard, S Target Inventory)

S Leadtime=7

S Order Quantity=IF THEN ELSE(Residual Lifetime<=(S Leadtime+M Leadtime+R Leadtime)*Leadtime Multiple, 0, MAX(0, S Inventory Adjustment+S Demand Forecasting))

S Profit=M Purchase*S Sale Price-S Inventory*S Inventory Holding Cost+S Discard*S Salvage Cost -S Purchase*S Supply Cost

S Purchase=S Order Quantity

S Safety Days=7

S Sale Price=4

S Salvage Cost=S Supply Cost*0.5

S Shipment=S Supply Line/S Leadtime

S Supply Cost=2

S Supply Line= INTEG (S Purchase-S Shipment,S Target Supply Line)

S Target Inventory=S Demand Forecasting*S Safety Days

S Target Supply Line=S Demand Forecasting*S Leadtime

Total Population=40000

Total Profit=M Profit+R Profit+S Profit

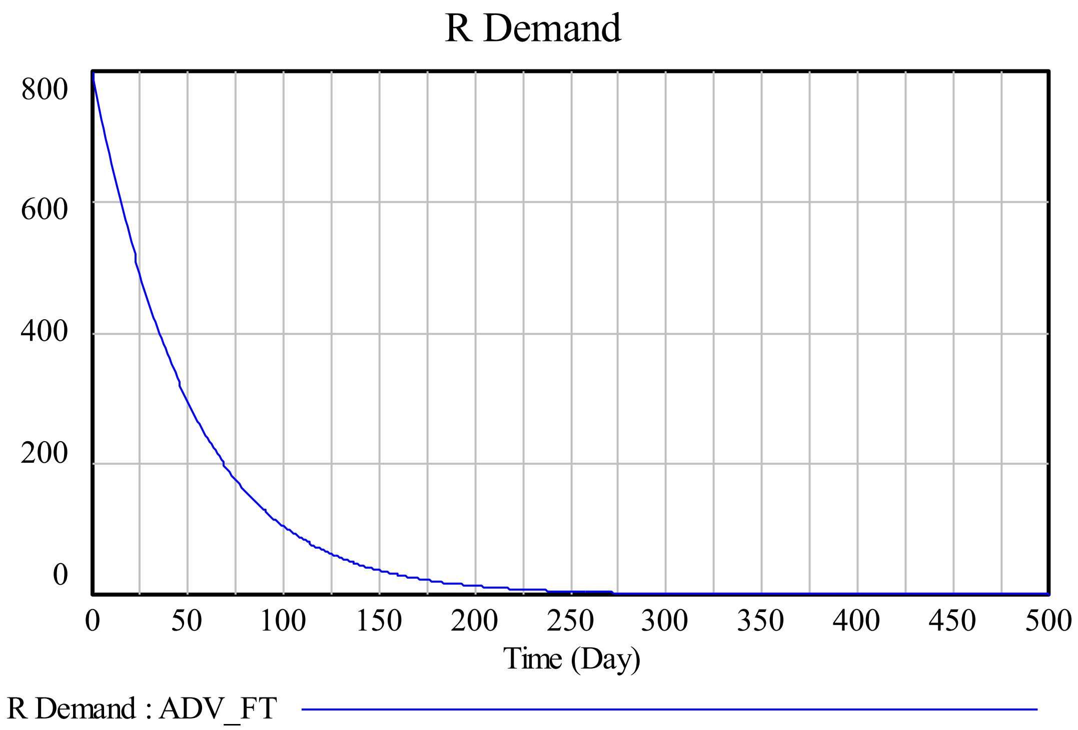
Word of Mouth Effect Ratio=0.001

The supplier (S) buys it for $2 and hands it over to M for $4. Inventory holding cost was estimated to be $0.1 per day for all supply chains.   Salvage cost was assumed to be half of the purchase cost. The interim participant (M) buys   for $4 and sells to R for $6, and R sells for the final $10.   The cost structure remains unchanged.

After modeling, optimization is performed. It is a matter of finding Real Finishtime and Leadtime Multiple that perform for   500 days and maximize supply chain profits.

AThe demand for DV products shows a pattern of initially increasing and decreasing day by day.

<Figure 13-3> Demand for ADV Products



In the case of ADV products, the oral effect is insignificant, and after more than 300 days, it converges to almost zero.   These products will depend on the margin structure, but it would be desirable to withdraw as early as possible.

We want to fix the purchase unit price or selling price of supply chain participants and change only the inventory maintenance cost to determine the optimal withdrawal time.   Vensim simulated when to stop   selling (set here   as the Real Finishtime variable) and when the supplier should stop buying. The lead time   for retailer (R) was fixed at 3 days   , manufacturer   (M) was fixed at 5 days, and supplier (S) was fixed at 7 days. So, on the supply chain side, the cumulative lead time of 15 days takes 15 days to reach the end customer. However, there are at least 15 days of safety stocks in the supply chain. Therefore, in order for profits to be maximized, suppliers must stop buying at least 30 days in advance. Of course, the timing of this will also be determined by the size of the inventory maintenance cost.

Table < 13-1> Simulation Results of Real Finishtime and End of Purchase of ADV Products

Inventory maintenance cost per unit	When to discontinue sales	End of purchase
0.10	500	437
0.20	500	246
0.21	470	276
0.22	463	271
0.23	466	265
0.24	496	117
0.25	496	99
0.26	429	154
0.27	233	1
0.28	234	1
0.30	234	1

If the inventory maintenance cost is $0.1, the inventory burden is relatively small. As a result of optimization, it was found that it was sold for 500 days, and the end of purchase was about 437 days. Since the decimal unit is cut, it is expressed as an approximate value. Even if the inventory maintenance cost is $0.2, it appears that the sale must be discontinued at 500 days, so the end does not actually end the sale. However, due to the high inventory burden, the end of purchase appears to be 246 days, which is half of the 500 days. Since the cost of maintaining inventory has doubled, the end of purchase has also been accelerated by almost 2 00 days. The amount purchased in 245 days means that profits can be maximized when the supply chain is open.

If the inventory maintenance cost increased to 0.3, the discontinuation time was pulled to 234 days, and the end of purchase was also pulled to 1 day. This means that with the inventory you built up before you started, the supply chain sells, and you no longer make purchases.

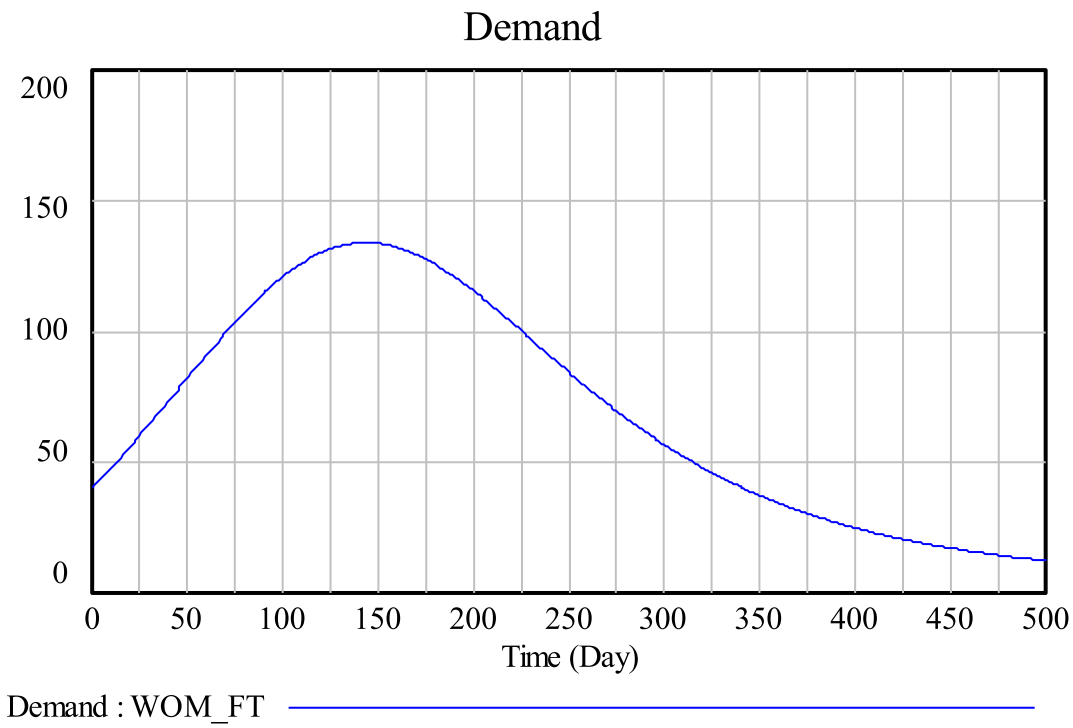
If the inventory maintenance cost is between 0.2 and 0.3 (this is not absolute. Relative weights for different margin structures must be calculated.) The timing of discontinuation and the end of purchase vary. For example, if the inventory maintenance cost is 0.24, you have to stop selling at 496 days, and the purchase must stop at 117 days. If the inventory maintenance cost is 0.27, the sale must be stopped on the 233rd day and the purchase must be terminated on the 1st. The problem is that there is not a single point where profits are maximized. This will be discussed in detail in WOM Products.

As a result, higher inventory maintenance costs speed up the time of discontinuation and the end of purchase. In particular, the speed at which the closing point of purchase is accelerated is very strong.

2) Exit strategy of WOM products

Unlike ADV products, WOM products have a very low advertising effect and a high oral effect. The demand for WOM products is shown in the following figure. The one-day advertising effect of the WOM product was assumed to be 0.001 and the one-day oral effect was assumed to be 0.02. It was assumed that there were 40,000 customers in total, and that 40,000 customers made a purchase once and then did not buy again.

<Figure 13-4> Demand for WOM products



5For 01 days (0 to 500 days), the average is 70.16 per day. The standard deviation is 41.29. As few as 12.32 units are sold (in 500 days) and 133.98 units are sold at as many (around 150 days). It is a pattern that leads through a short introduction phase, a growth phase, and a short maturity period to a period of decline.

<Table 13-2> Discontinuation and End of Purchase of WOM Products

Inventory maintenance cost per unit	When to discontinue sales	End of supplier purchase
0.1	500	470
0.2	500	466
0.3	500	464
0.4	500	260
0.4	482	275
0.4	494	260
0.5	500	110
0.5	460	155
0.5	428	185
0.5	403	215
0.5	372	245
0.5	365	245
0.6	497	50
0.6	357	185
0.6	500	50
0.6	481	65
0.6	425	125
0.6	348	200
0.6	363	185
0.6	292	245
0.6	313	245
0.7	447	65
0.7	500	65
0.7	326	185
0.7	388	125
0.7	262	245
0.8	413	95
0.8	443	65
0.8	318	185
0.8	500	5

0.8	381	125
0.8	257	245
0.9	473	35
0.9	255	250.25
1	251	5
1	282	80
1	282	5
1	227	1
1	290	1
1	229	125

Even in WOM products, when inventory maintenance costs rise, the time of discontinuation tends to be accelerated. ACompared to DV products, the speed at which the supplier's purchase cessation time is accelerated is not high.

If the inventory maintenance cost is $0.1, it turns out that the inventory burden is low, so it is sold to the end without a stop time for sale, and the point where the purchase stop is 470 days is the point where the profit is maximized. 470 days is twice the cumulative lead time (15 days).

Even if the cost of maintaining inventory goes up to $0.2 or $0.3, selling until the end helps the profit. This means that the cost of maintaining inventory is not greatly burdened. However, we can see that the time to stop buying is getting faster and faster. At an inventory maintenance cost of $0.2, it was 500 days at the point of discontinuation and 466 days at the time of discontinuation. If the inventory maintenance cost is $0.4, the same discontinuation time is 500 days, but the discontinuation time is 260 days, as shown in <Table 13-2> of Table 13-2.

However, when the simulation is carried out, it can be seen that many optimal alternatives appear. If the inventory maintenance cost is 0.4, the end of sale appears between 494 and 500 days. And the discontinuation period is 260 to 275 days. This segment shows that supply chain profits vary greatly.

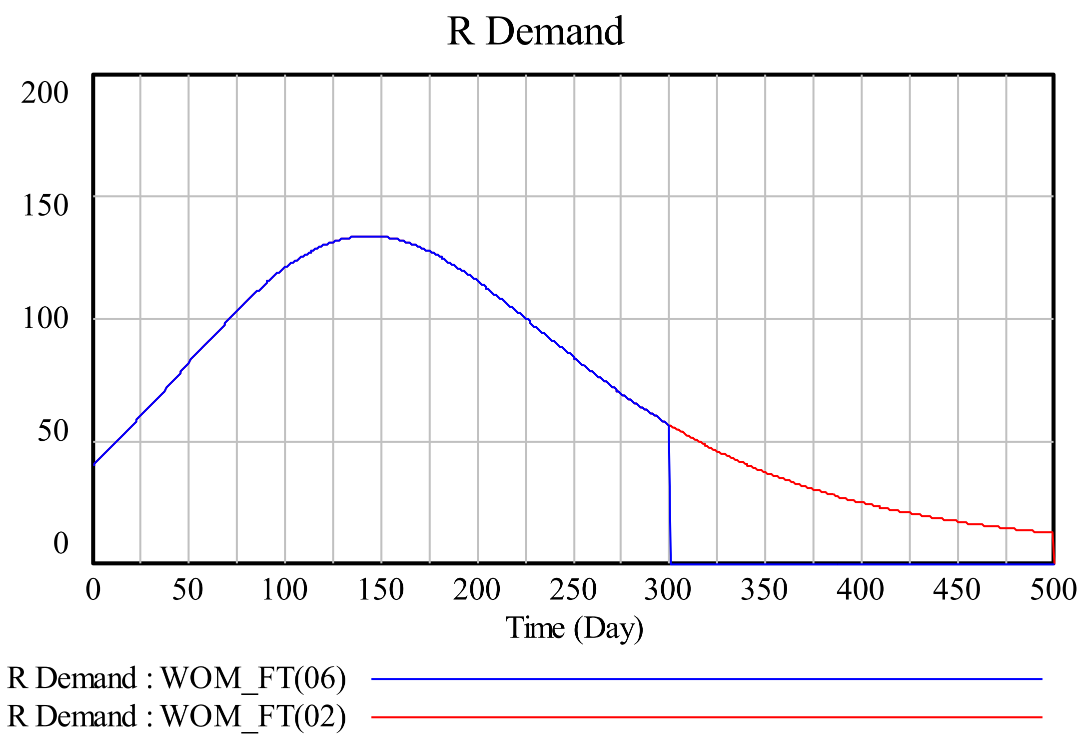
If the cost of maintaining inventory rises to 0.5, the spread becomes even greater. It's a good idea to stop buying at 110 days and sell by 5 00 days, which means that if you want to stop selling in 460 days, you have to stop buying in about 185 days.

It even happens the other way around, with a $0.5 inventory maintenance cost, end of sale at 365 days, and stop purchase at 245 days. These are all possible alternatives, indicating that multiple walls can exist. This is because there is a trade-off between the cost of inventory and the burden of increasing profits from sales.

Consider the case where the cost of maintaining inventory per unit is $0.7. 4 There are cases where the sale ends on the 47th and the purchase is discontinued on the 125th. This means that operating with the remaining inventory in the supply chain for more than 300 days can be an alternative to boosting profits. Even with the same inventory maintenance cost, there are cases where the end of sale is 500 days and the purchase stop is 65 days. This means that if you buy it by 65 days and sell it up to 500 days, your profit will be maximized.

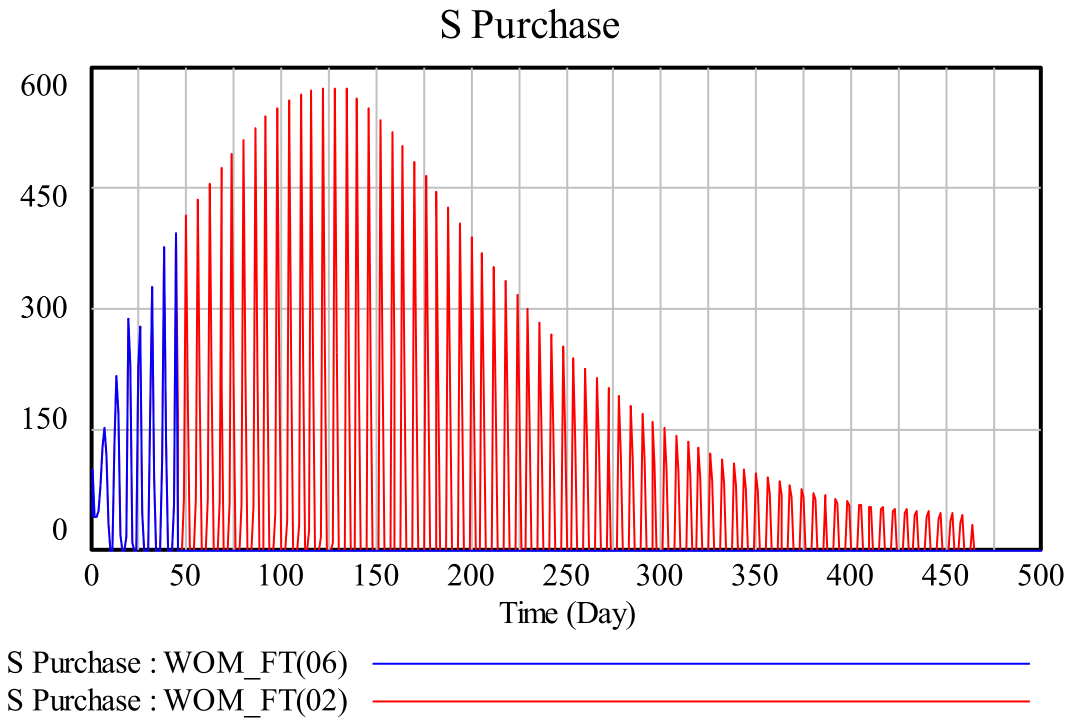
Part of the inventory maintenance cost 0.2 and 0.6 in WOM product is explained as an example. The demand for these products is shown in the following figure.

<Figure 13-5> 2 Demand for WOM products



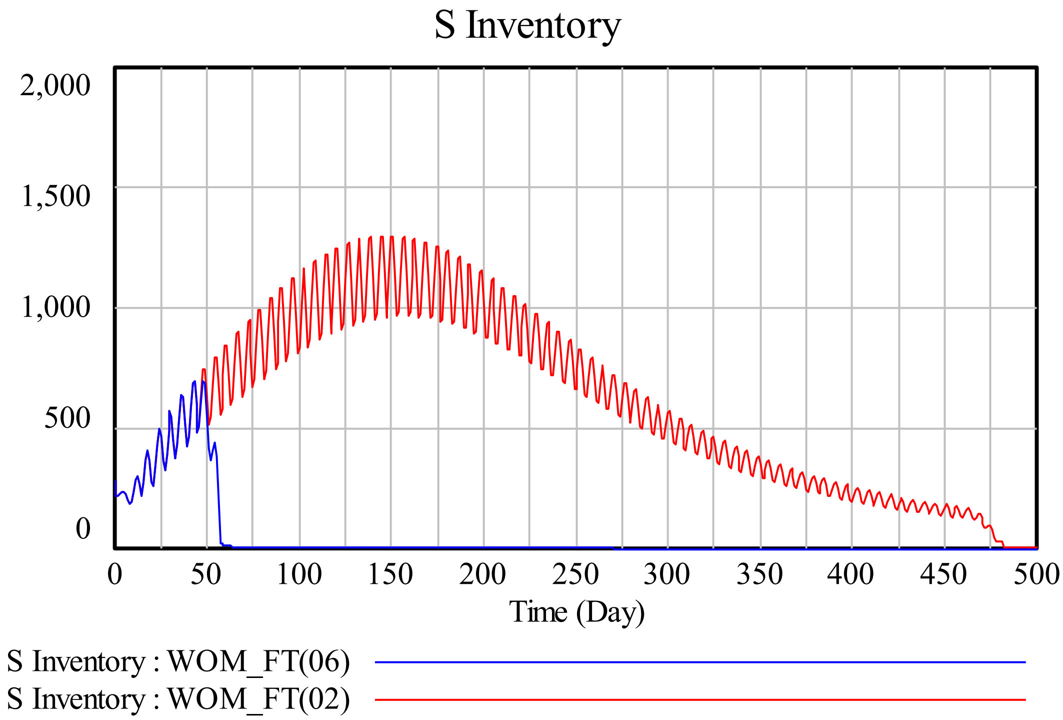
One optimal plan (WOM_FT (06)) with an inventory maintenance cost of 0.6 is the blue line and stops selling at 300 days. The red line, on the other hand, has an inventory maintenance cost of 0.2 and continues to sell up to 500 days. On the other hand, if we look at the supplier's purchase volume (S Purchase), it is shown in the following figure.

<Figure 13-6> S Purchase of 2 WOM



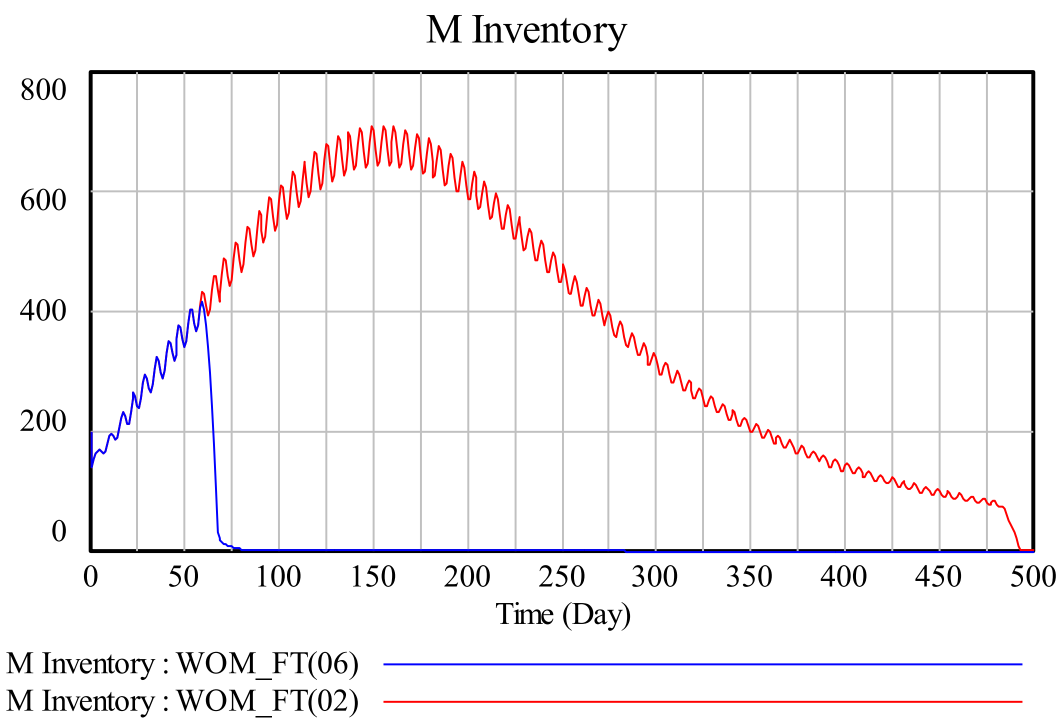
One case with an inventory maintenance cost of 0.2 ended the purchase around 460, and one case with an inventory maintenance cost of 0.6 (blue line) stopped buying around 50 days. In terms of profits, supply chain profits vary greatly depending on inventory maintenance costs. If the inventory maintenance cost is 0.6, the total profit per day is only about $23. On the other hand, if the inventory maintenance cost is 0.2, the average supply chain profit is about $336 per day. It means that the blue line has a high cost of maintaining inventory, so it is efficient to stop selling early. This means that increasing the sales period will not improve profits.

<Figure 13-7> S   stock of 2 WOM products



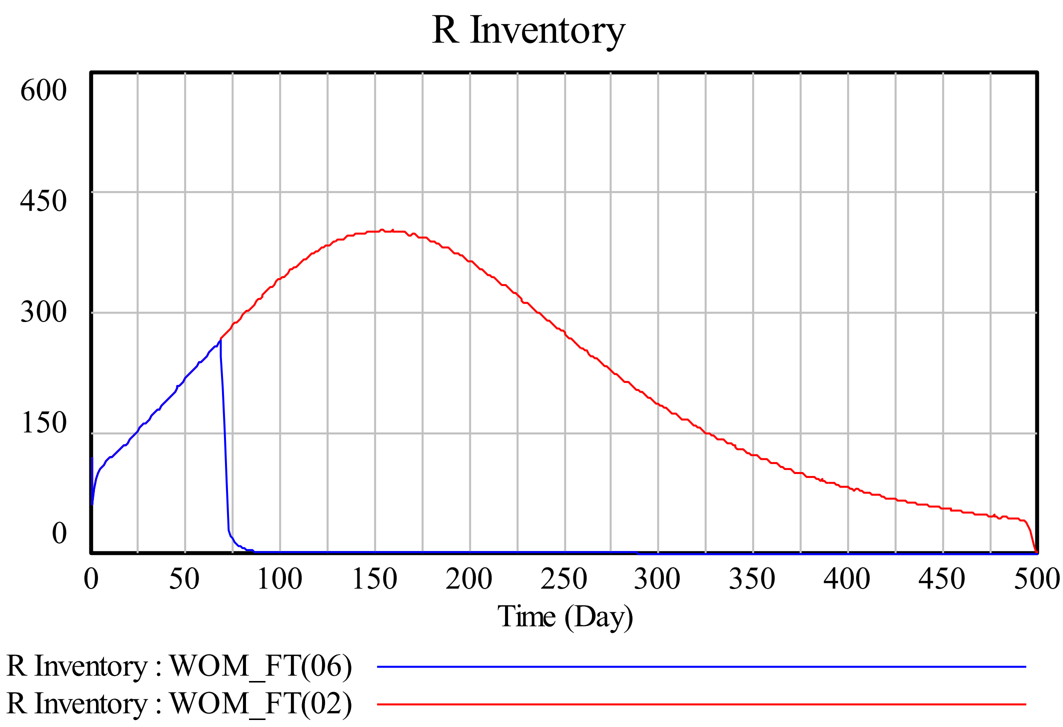
If you look at the inventory of S, in the case of the blue line, the stock goes to zero because the purchase stops early (about 60 days), and no further supply occurs. In the case of the red line, it is only at the end that the stock goes towards zero. At this time, of course, the retailer (R) is selling.

<Figure 13-8> M stock of 2 WOM



The inventory of the manufacturer (M) in the middle of the supply chain is similar to that of S. However, the point where the inventory goes to zero is after the S inventory.

<Figure 13-9> R stock of 2 WOM



Retail inventory is relatively smooth. In the case of the blue line, sales have stopped at about the 80-day line. In the case of the red line, sales are carried out until the point of close to 500 days.

On the other hand, when the total cost is reflected in the inventory shortage cost of R, the following result can be obtained. Here, R's inventory shortage reflects twice the inventory maintenance cost, so S and M's inventory shortage does not help create fundamental value. In this way, if R's inventory shortage cost is reflected in the gross profit and optimized, the premature cessation of sales is eliminated. It is pushed back to the optimal point. However, there is a disadvantage that the cost of losing customers due to the loss of sales opportunities is overestimated. In the modeling of product demand, a condition was placed that no repurchase occurs. Accounting for the cost of losing a customer when a repeat purchase cannot be made is a family violation. It is only a reference. The advantage is that the optimal discontinuation time and the optimal end of purchase are made at a single point.

Table 13-3> < Gross profit reflects R's under-stock cost (twice the inventory maintenance cost), when to discontinue sales and end of purchase due to the inventory maintenance cost of WOM products

Inventory maintenance costs	When to discontinue sales	Supplier's End of Purchase
0.1	500	470
0.2	498	467
0.3	498	467
0.4	328	468.5
0.5	136	473
0.6	60	473
0.7	38	475.55
0.8	29	477.8
0.9	22	0.5
1	22	65

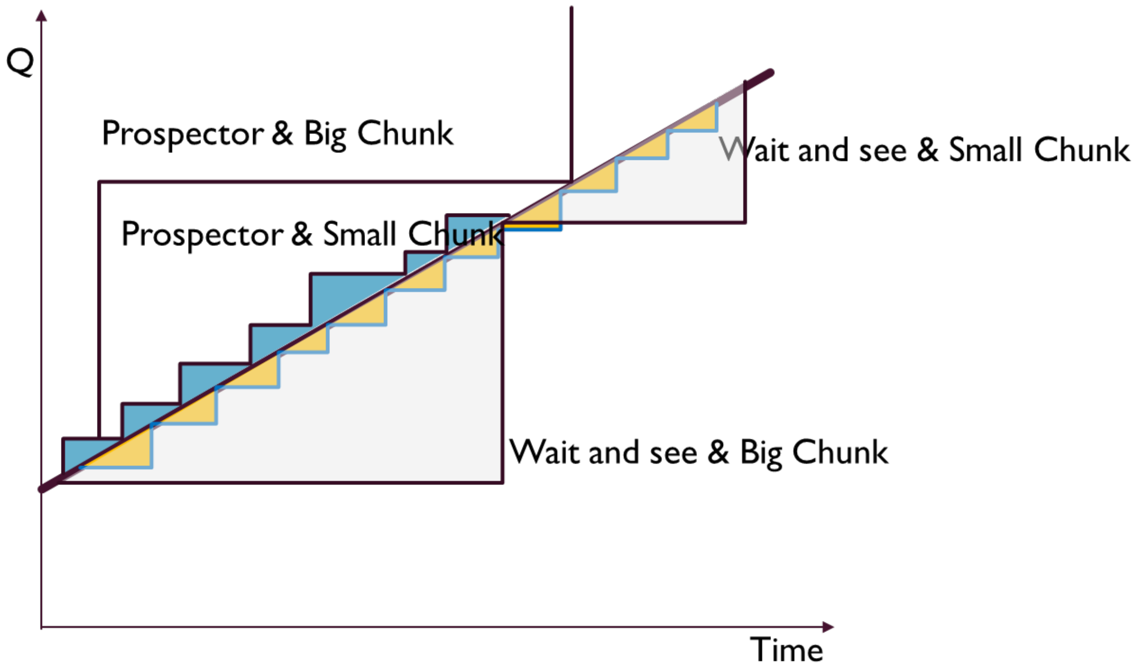
1Chapter 4

Transportation Capacity Management

Transportation Capacity Management

The proportion of transportation costs in logistics activities is absolute. It varies from industry to industry, but transportation costs can account for more than 80% of logistics costs. In supply chains, it is often assumed that transportation is seamless, but in practice, transport capacity often constrains supply capacity. Moreover, managing capacity takes more time and effort, and is costly if misjudged. For example, when the whip effect occurs, the transport requirement suddenly increases. You can't suddenly have 1,000 units that were kept at 100.

<Figure 14-1> Capability Strategies



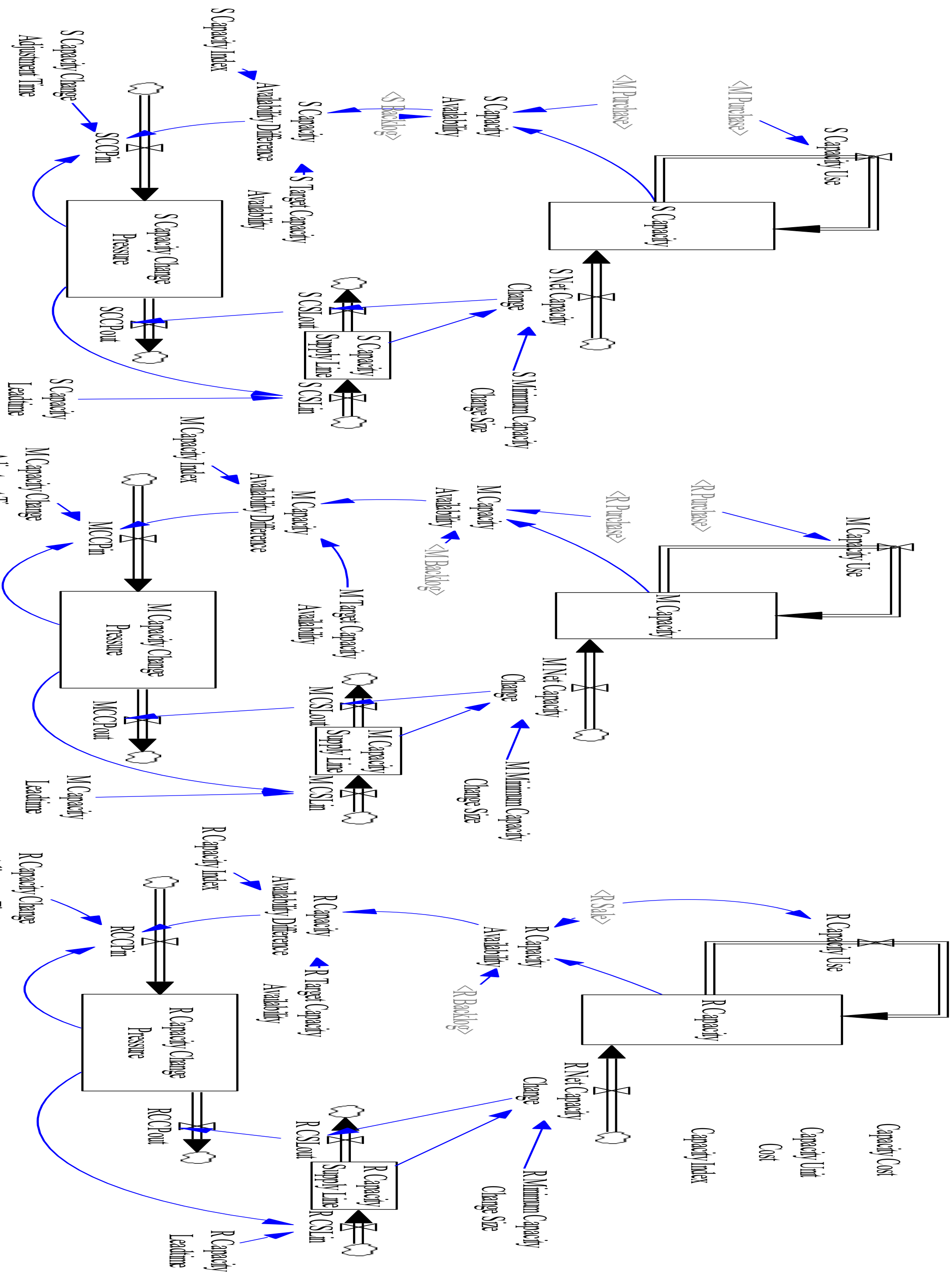
There are four main types of capability strategies. Expanding or contracting abilities in advance is called prospector, and feeling the need and following belatedly is called waiting and seeing. And when you increase or decrease your abilities, you can choose a large amount at once with your big feet (big chunk; Hereinafter, large-scale capacity expansion), small chunks; hereinafter referred to as small capacity expansion).

There are four possible strategies, but in this chapter we will only look at the size of the capacity expansion. In the three-stage supply chain (SMR), each person looks at how best to size their capacity expansion.

1) Model for Competency Management

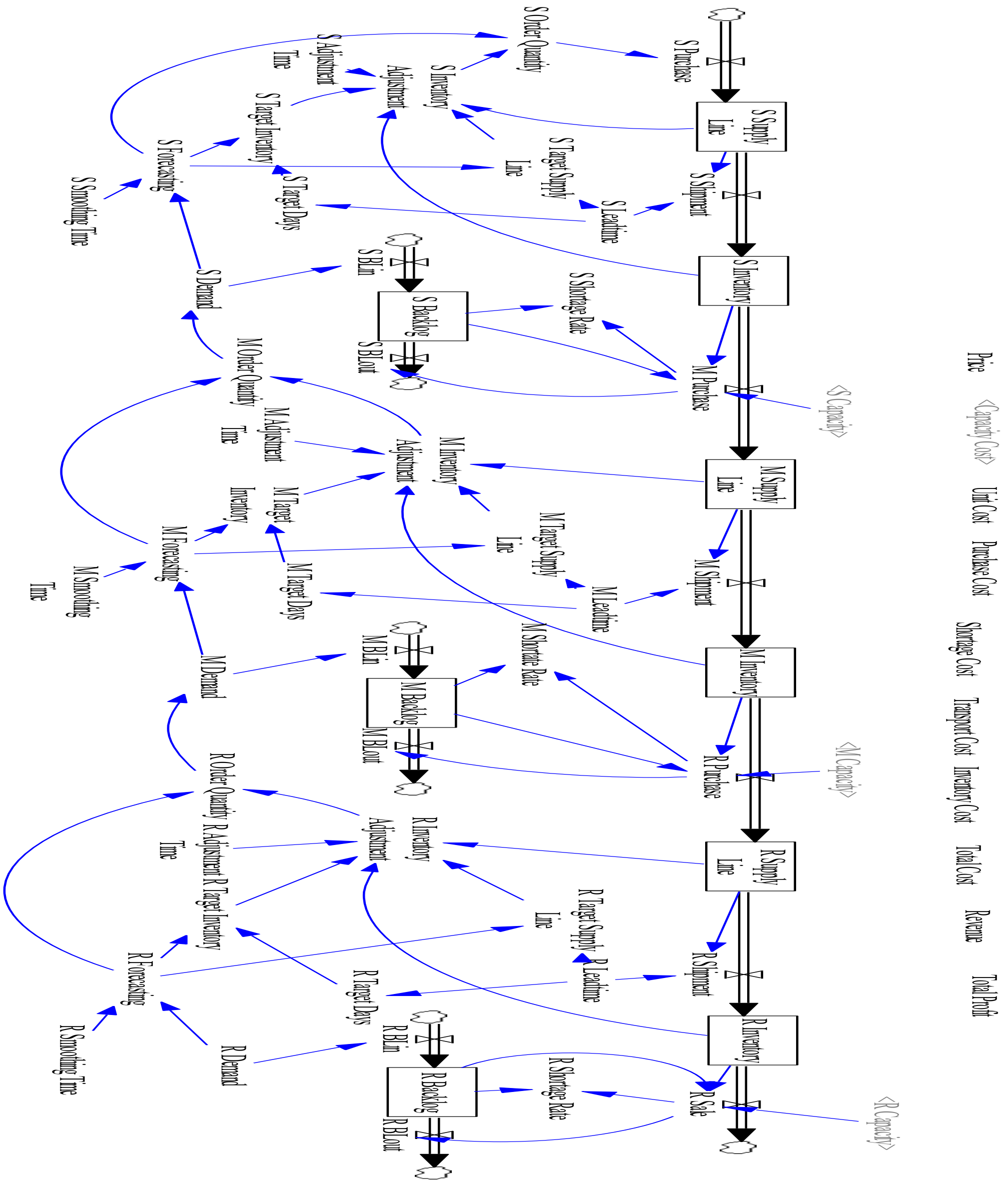
It brings the same three-stage supply chain that we have covered many times so far. Then build the following model:

<Figure 14-2> Competency Management Module



And for reference, the model for the supply chain is as follows.

<Figure 14-3> Supply Chain Module



The relationship between the variables used in the two-layer model is as follows.

Capacity Cost=(M Capacity+R Capacity+S Capacity)*Capacity Unit Cost

Capacity Index= 10

Capacity Unit Cost=100

Inventory Cost= M Inventory+R Inventory+S Inventory

M Adjustment Time=5

M Backlog= INTEG (M BLin-M BLout,100)

M BLin=M Demand

M BLout=R Purchase

M Capacity Availability Difference=(M Target Capacity Availability-M Capacity Availability)*M Capacity Index

M Capacity Availability= XIDZ(M Capacity, R Purchase+M Backlog, 1)

M Capacity Change Adjustment Time=3

M Capacity Change Pressure= INTEG (MCCPin-MCCPout,0)

M Capacity Index=Capacity Index

M Capacity Leadtime=3

M Capacity Supply Line= INTEG (M CSLin-M CSLout,0)

M Capacity Use=R Purchase

M Capacity= INTEG (M Net Capacity Change+M Capacity Use-M Capacity Use,200)

M CSLin=M Capacity Change Pressure/M Capacity Leadtime

M CSLout=M Net Capacity Change

M Demand=R Order Quantity

M Forecasting=SMOOTH(M Demand, M Smoothing Time)

M Inventory Adjustment=(M Target Supply Line-M Supply Line+M Target Inventory-M Inventory)/M Adjustment Time

M Inventory= INTEG (M Shipment-R Purchase,M Target Inventory)

M Leadtime=5

M Minimum Capacity Change Size=10

M Net Capacity Change=IF THEN ELSE(M Capacity Supply Line>M Minimum Capacity Change Size, M Minimum Capacity Change Size, IF THEN ELSE(M Capacity Supply Line<-M Minimum Capacity Change Size, -M Minimum Capacity Change Size, 0))

M Order Quantity=MAX(0, M Forecasting+M Inventory Adjustment)

M Purchase=MIN(S Capacity, MIN(S Backlog, S Inventory))

M Shipment=M Supply Line/M Leadtime

M Shortate Rate=MAX(0, M Backlog-R Purchase)

M Smoothing Time=5

M Supply Line= INTEG (M Purchase-M Shipment,M Target Supply Line)

M Target Capacity Availability=1

M Target Days= M Leadtime

M Target Inventory=M Forecasting*M Target Days

M Target Supply Line=M Forecasting* M Leadtime

MCCPin=(M Capacity Availability Difference-M Capacity Change Pressure)/M Capacity Change Adjustment Time

MCCPout=M CSLout

Price=2000

Purchase Cost= S Purchase*Unit Cost

R Adjustment Time=3

R Backlog= INTEG (R BLin-R BLout,100)

R BLin= R Demand

R BLout=R Sale

R Capacity Availability Difference=(R Target Capacity Availability-R Capacity Availability)*R Capacity Index

R Capacity Availability= XIDZ(R Capacity, R Sale+R Backlog, 1)

R Capacity Change Adjustment Time=5

R Capacity Change Pressure= INTEG (RCCPin-RCCPout,   0)

R Capacity Index=Capacity Index

R Capacity Leadtime=3

R Capacity Supply Line= INTEG (R CSLin-R CSLout,0)

R Capacity Use=R Sale

R Capacity= INTEG (R Net Capacity Change+R Capacity Use-R Capacity Use,200)

R CSLin=R Capacity Change Pressure/R Capacity Leadtime

R CSLout=R Net Capacity Change

R Demand=(100+STEP(100, 31))

R Forecasting=SMOOTH(R Demand, R Smoothing Time)

R Inventory Adjustment=(R Target Inventory-R Inventory+R Target Supply Line-R Supply Line)/R Adjustment Time

R Inventory= INTEG (R Shipment-R Sale,R Target Inventory)

R Leadtime=3

R Minimum Capacity Change Size=10

R Net Capacity Change=IF THEN ELSE(R Capacity Supply Line>R Minimum Capacity Change Size, R Minimum Capacity Change Size, IF THEN ELSE(R Capacity Supply Line<-R Minimum Capacity Change Size, -R Minimum Capacity Change Size, 0))

R Order Quantity=MAX(0, R Forecasting+R Inventory Adjustment)

R Purchase=MIN(M Capacity, MIN(M Inventory, M Backlog))

R Sale=MIN(R Backlog, MIN(R Capacity, R Inventory))

R Shipment=R Supply Line/R Leadtime

R Shortage Rate=MAX(0, R Backlog-R Sale)

R Smoothing Time=3

R Supply Line= INTEG (R Purchase-R Shipment,R Target Supply Line)

R Target Capacity Availability=1

R Target Days= R Leadtime

R Target Inventory=R Forecasting*R Target Days

R Target Supply Line=R Forecasting*R Leadtime

RCCPin=(R Capacity Availability Difference-R Capacity Change Pressure)/R Capacity Change Adjustment Time

RCCPout=R CSLout

Revenue=R Sale*Price

S Adjustment Time=7

S Backlog= INTEG (S BLin-S BLout,100)

S BLin= S Demand

S BLout=M Purchase

S Capacity Availability Difference=S Capacity Index*(S Target Capacity Availability-S Capacity Availability)

S Capacity Availability= XIDZ(S Capacity, M Purchase+S Backlog, 1)

S Capacity Change Adjustment Time=3

S Capacity Change Pressure= INTEG (SCCPin-SCCPout, 0)

S Capacity Index=Capacity Index

S Capacity Leadtime=3

S Capacity Supply Line= INTEG (S CSLin-S CSLout,0)

S Capacity Use=M Purchase

S Capacity= INTEG (S Net Capacity Change+S Capacity Use-S Capacity Use,200)

S CSLin=S Capacity Change Pressure/S Capacity Leadtime

S CSLout=S Net Capacity Change

S Demand=M Order Quantity

S Forecasting=SMOOTH(S Demand, S Smoothing Time)

S Inventory Adjustment=(S Target Inventory-S Inventory+S Target Supply Line-S Supply Line)/S Adjustment Time

S Inventory= INTEG (S Shipment-M Purchase,S Target Inventory)

S Leadtime=7

S Minimum Capacity Change Size=10

S Net Capacity Change=IF THEN ELSE(S Capacity Supply Line>S Minimum Capacity Change Size, S Minimum Capacity Change Size, IF THEN ELSE(S Capacity Supply Line<-S Minimum Capacity Change Size, -S Minimum Capacity Change Size, 0))

S Order Quantity=MAX(0, S Inventory Adjustment+S Forecasting)

S Purchase=S Order Quantity

S Shipment=S Supply Line/S Leadtime

S Shortage Rate=MAX(0, S Backlog-M Purchase)

S Smoothing Time=7

S Supply Line= INTEG (S Purchase-S Shipment,S Target Supply Line)

S Target Capacity Availability=1

S Target Days=S Leadtime

S Target Inventory=S Forecasting*S Target Days

S Target Supply Line=S Forecasting*S Leadtime

SCCPin=(S Capacity Availability Difference-S Capacity Change Pressure)/S Capacity Change Adjustment Time

SCCPout=S CSLout

Shortage Cost=R Shortage Rate*9

Total Cost=Inventory Cost+Transport Cost+Shortage Cost+Capacity Cost+Purchase Cost

Total Profit=Revenue-Total Cost

Transport Cost=(INTEGER(M Purchase)+1+INTEGER(R Purchase)+1+INTEGER(S Purchase)+1)*100

Unit Cost=100

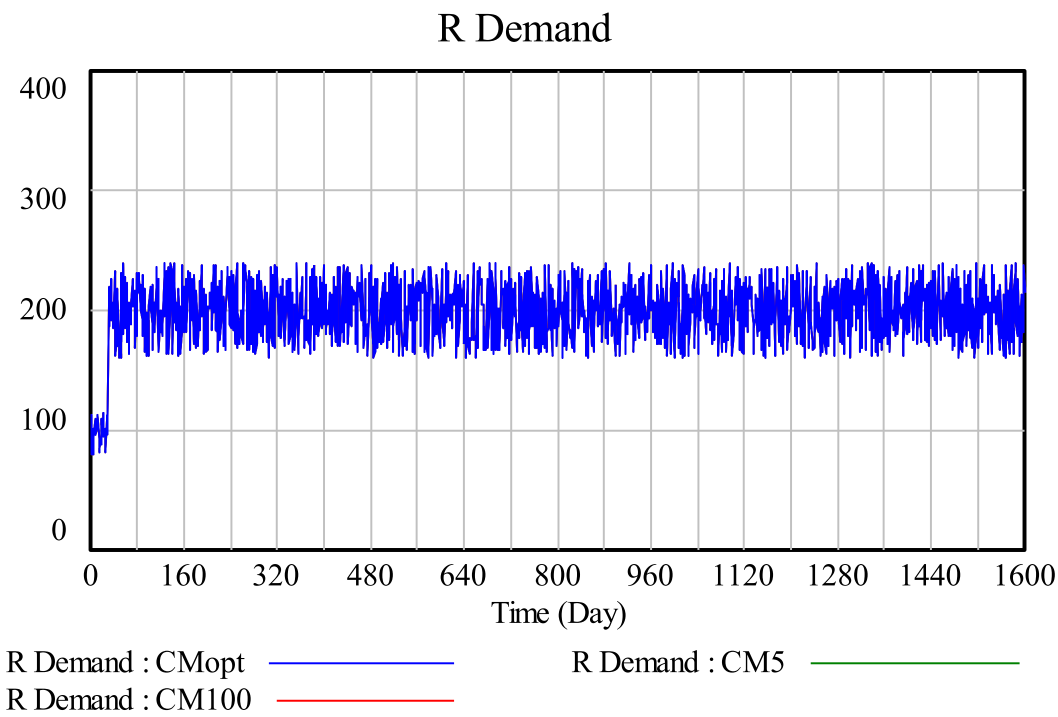
FINAL TIME = 1600 ~ Day

INITIAL TIME = 0 ~ Day

IME STEP = 1 ~ Day

The demand for R is shown in the following figure. There was a sharp change from 100 to 200 in the early days, and from the 31st to the 1600th it remained at an average of 200.

<Figure 14-4> Demand for R in Supply Chains

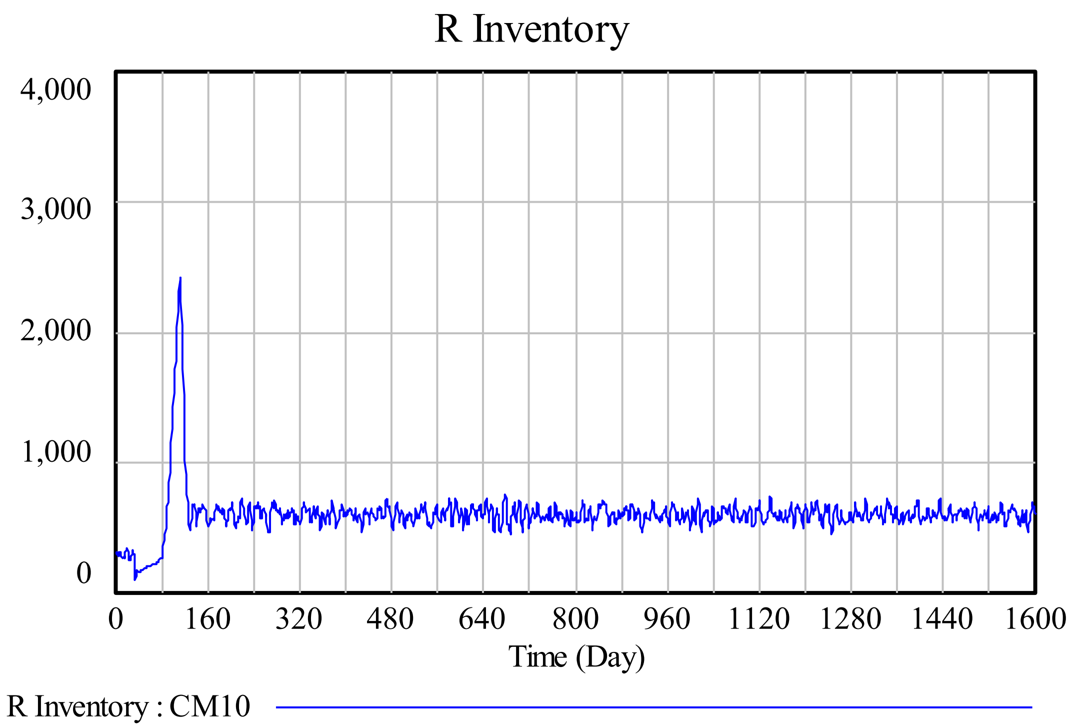


The supply chain module is almost identical to the one discussed in the previous chapter. It was assumed that capacity (e.g., transport trucks) was constrained in inventory, and that the cost of maintaining capacity in gross cost and gross profit was $100 per day. The sale price was assumed to be $2,000.

In the capability management module , the adjustment time of S, M, and R and the capacity leadtime were all assumed to be the same 3 days. In the supply chain module, the rhythm of S MR is assumed to be 7 days, 5 days, and 3 days, respectively, but in the capability management module, it is limited to 3 days to avoid complexity. You can give differentials as needed.

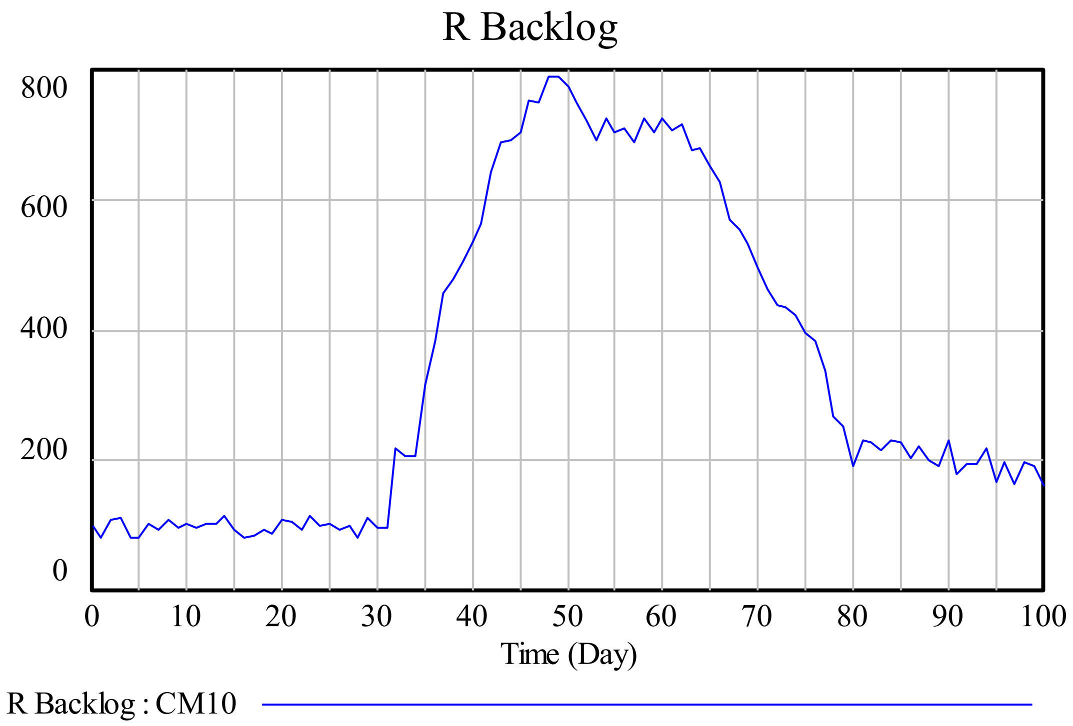
The simulation file was named CM10, CM100, CMopt, etc. In capacity management, the size of the chunk is 10 and 100. The one with opt at the end is the result file according to the optimization. In the case of the CM10, 10 trucks are introduced at a time, and then 10 trucks are sent out.

<Figure 14-5> R Inventory at C M10



The demand for R averages 100 from 30 days and 200 from 31 days to 1600 days. A one-way distribution (0.8, 1.2) was applied. It was performed on only one seed. What is unusual about R Inventory is that demand jumped on the 31st, and inventory peaked at 1,000 days. It is judged to be the result of limited transport capacity. With the surge in backrock, M wanted to increase the volume of deliveries, but the number of trucks was insufficient, so it remained as backgreen. This also happens when R fulfills an order to the end customer.

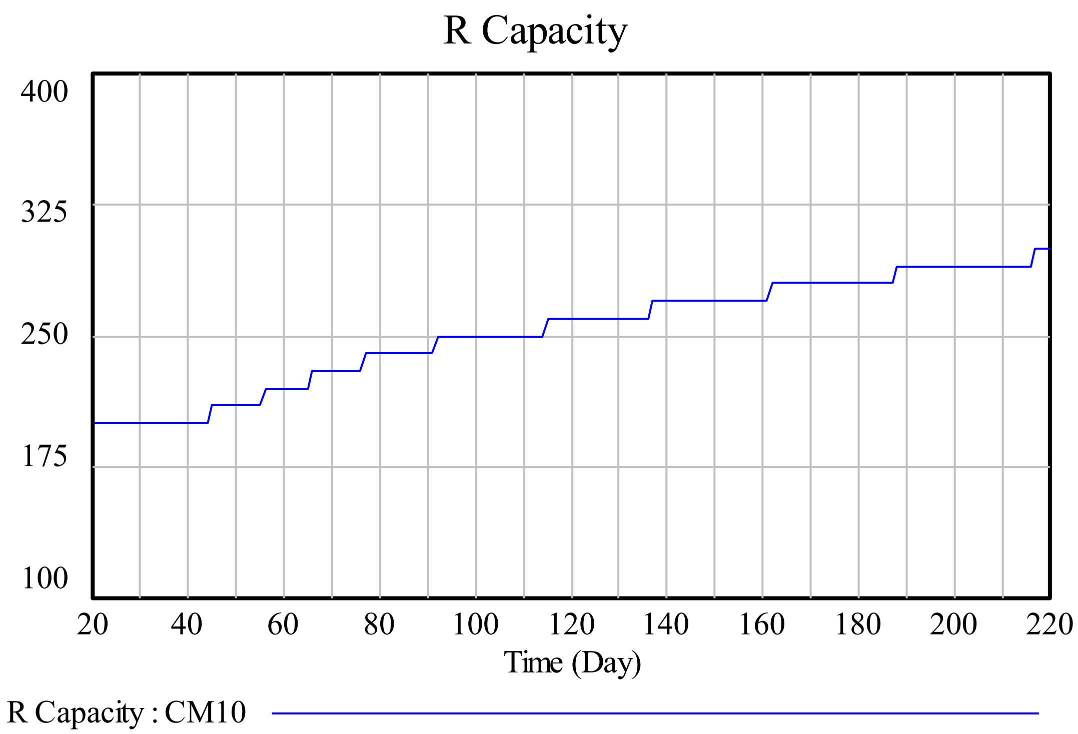
<Figure 14-6> R Backlog at C M10



R Backlog increases sharply after demand spikes on the 31st. It peaks on the 49th and then begins to decline. The R backlog returns to normal value 200 until 80 days. After the R backlog normalizes, the R Inventory increases rapidly and it takes a considerable amount of time for this to normalize. The delay when R Inventory appears continuously in R Backlog is due to capacity constraints.

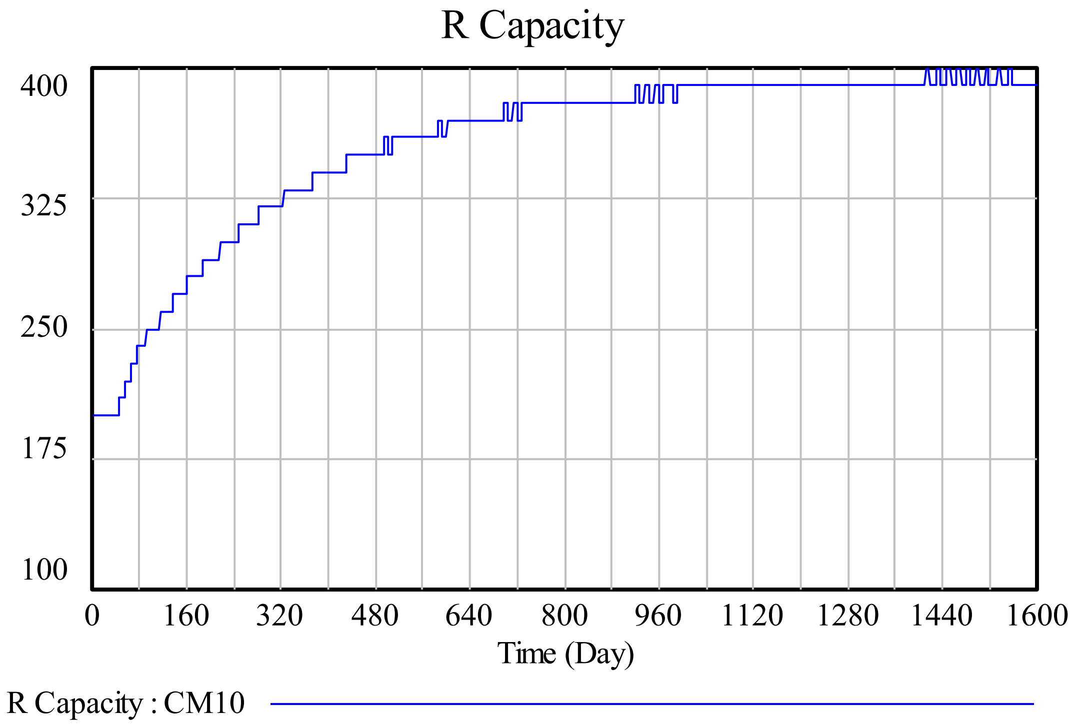
The transport capacity at this time is shown in the following figure.

<Figure 14-7>　Change in R capacity (between 25 and 300 days)



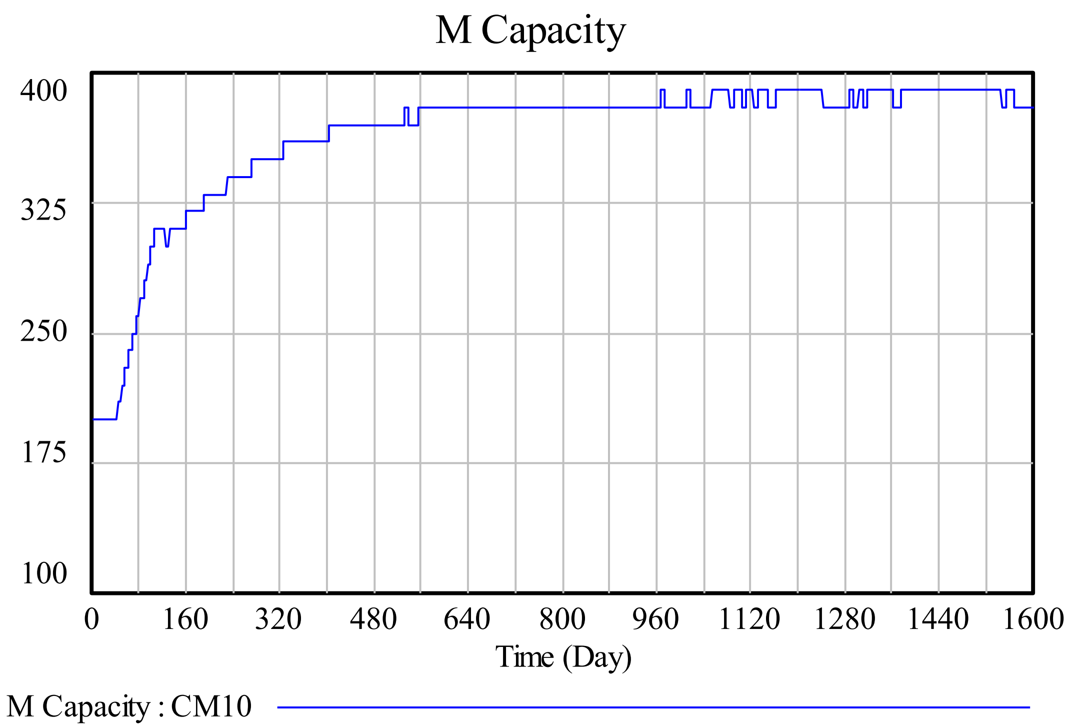
Capacity increased from 200 at first to 300 in 220 days. The continued upward trend of transport capacity needs to be carefully monitored.

<Figure 14-8> R Capacity for the entire period



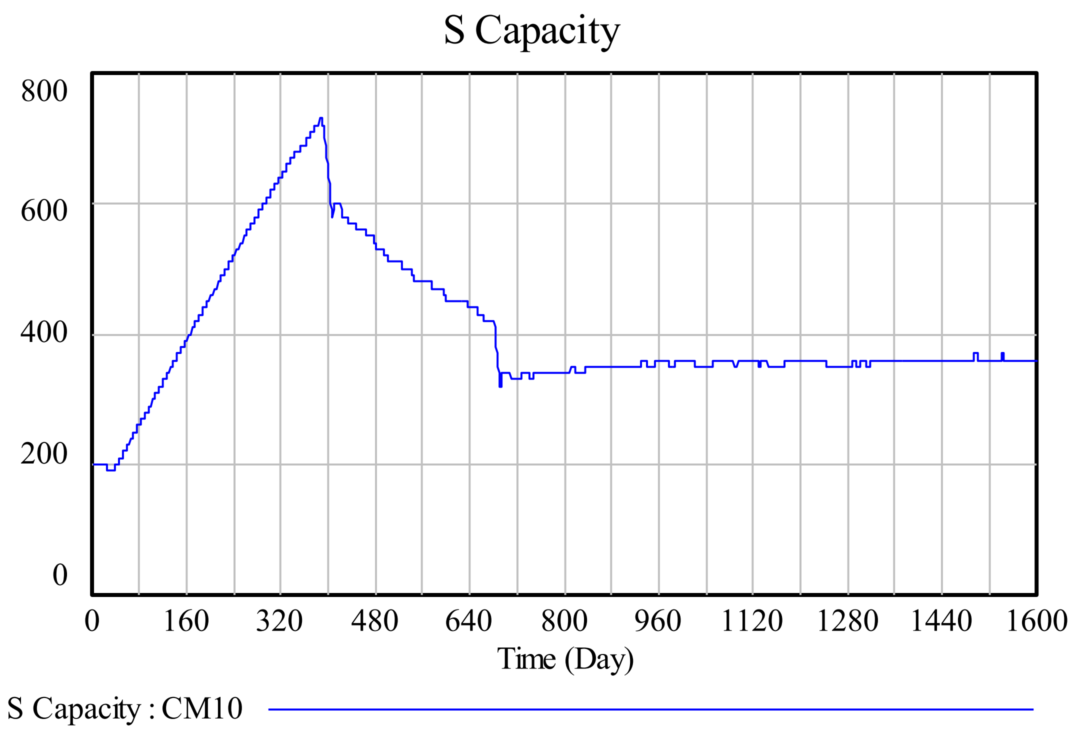
It started with the initial 200s and continues to 4 00s. However, if the chunk size is 10 for a wait-and-see approach, approaching 400 (the optimal point) is when 1,000 days are reached. It's a slow move.

<Figure 14-9> Changes in M　Capacity Over Time



Compared to　R capacity, M capacity converges a little faster, but it still takes a considerable amount of time (about 600 days) to converge.

<Figure 14-10> Changes in S Capacity Over Time

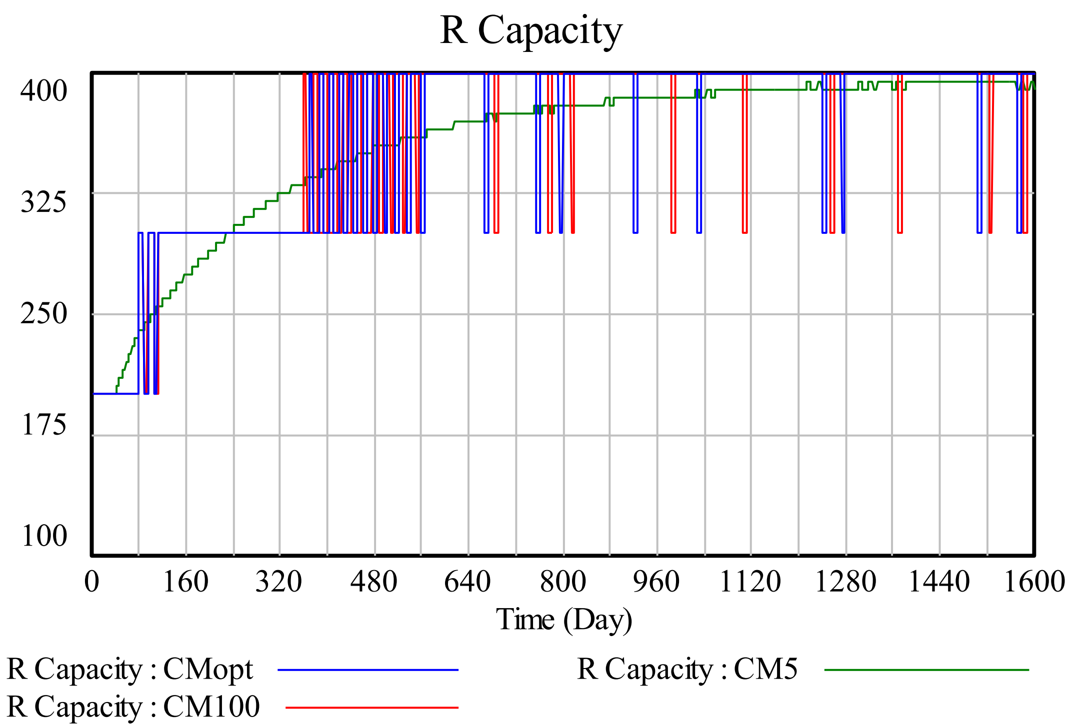


S Capacity increases steadily up to 400 days. It plummets. It leads to a decline again, and it is not until 700 days that it returns to balance. This slowness is due to the size of the chunk.

2) Performance comparison according to size of capacity expansion (Chunk)

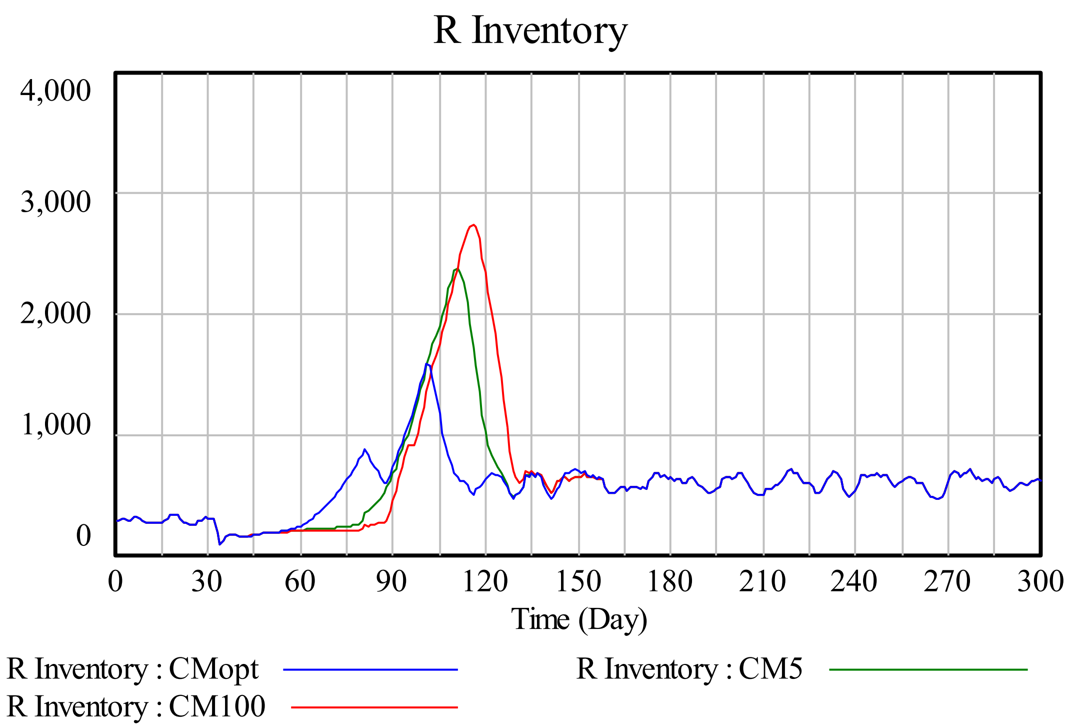
Compare the size of the capability expansion with the optimization period. Compare the size of RMS's capacity expansion with 100 units and 5 units uniformly and the size of the capacity expansion with the maximum gross profit. They are CM100, CM5, and CMopt in order. CMopt's R Minimum Capacity Change Size was 100, M Minimum Capacity Change Size was 36.2706, and S Minimum Capacity Change Size = 1.85513.

<그림 14-11> CM5, CM100, CMopt의 R Capacity



Compared to CM5, CM100 was analyzed to find a balance point quickly. Since CMop has an R Minimum Capacity Change Size of 100, CM100 and CMopt are almost identical. The fact that T1 00 goes back and forth between 300 and 400 after 400 days is due to daily changes in demand.

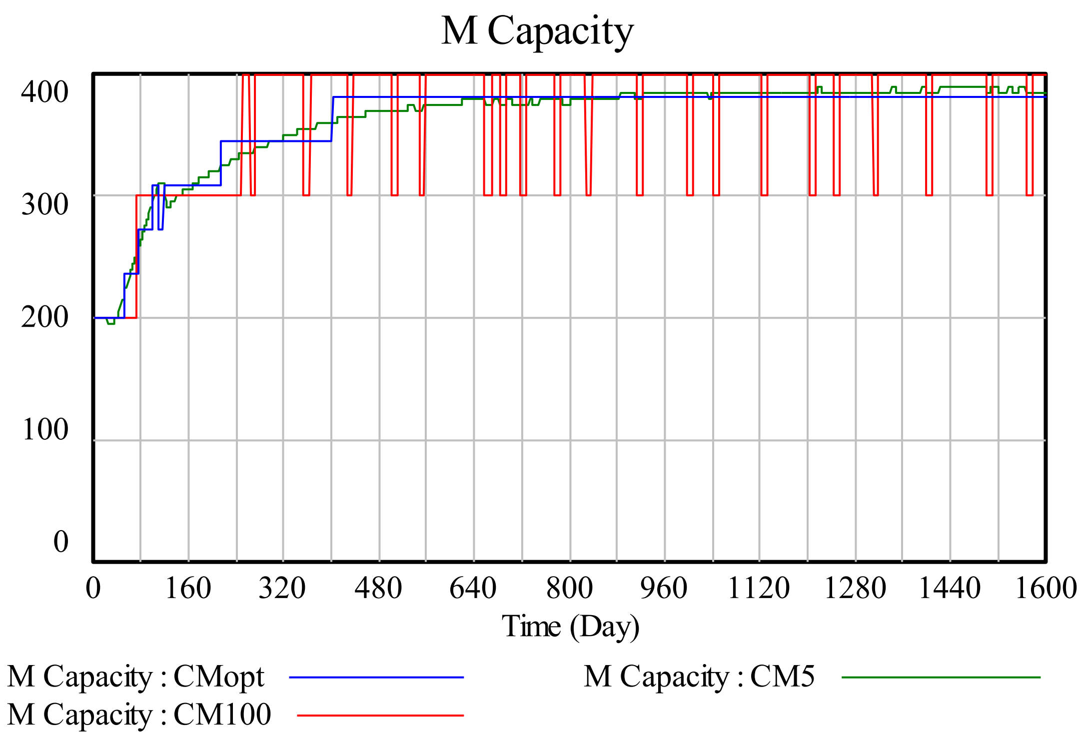
<그림 14-12> CM5, CM100, CMopt의 R Inventory(0-300일)



CMopt had the smallest whip effect and the fastest time finding the equilibrium. On the other hand, the CM100 was found to be the slowest. Between 301 and 1600 days, it was found to be the same.

M Capacity is shown in the following figure.

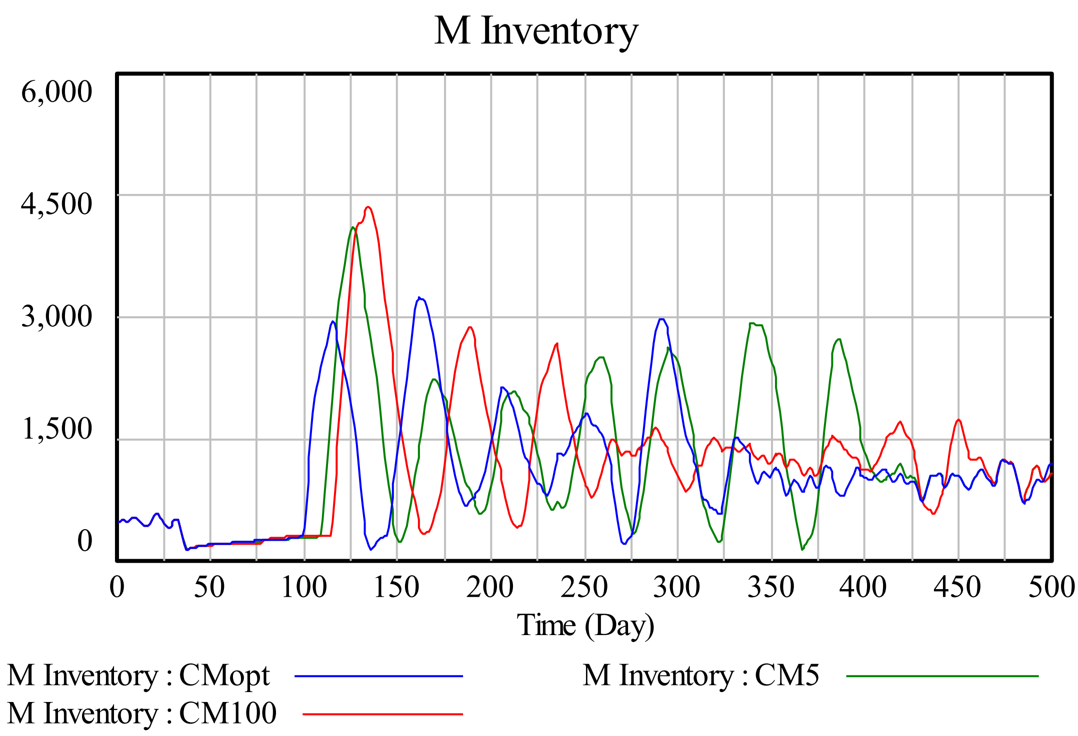
<그림 14-13> CM5, CM100, CMopt의 M Capacity



The CM100 and CMopt found the equilibrium point relatively quickly, while the CM5 was the last. The average M capacity was 361.98 units for CMopt, 367.70 units for CM100, and 362.17 units for CM5. Considering that CMopt's M Minimum Capacity Change Size is about 36 units, it can be said that the larger the size, the faster the balance point is found.

M Inventory according to M Capacity is as follows:

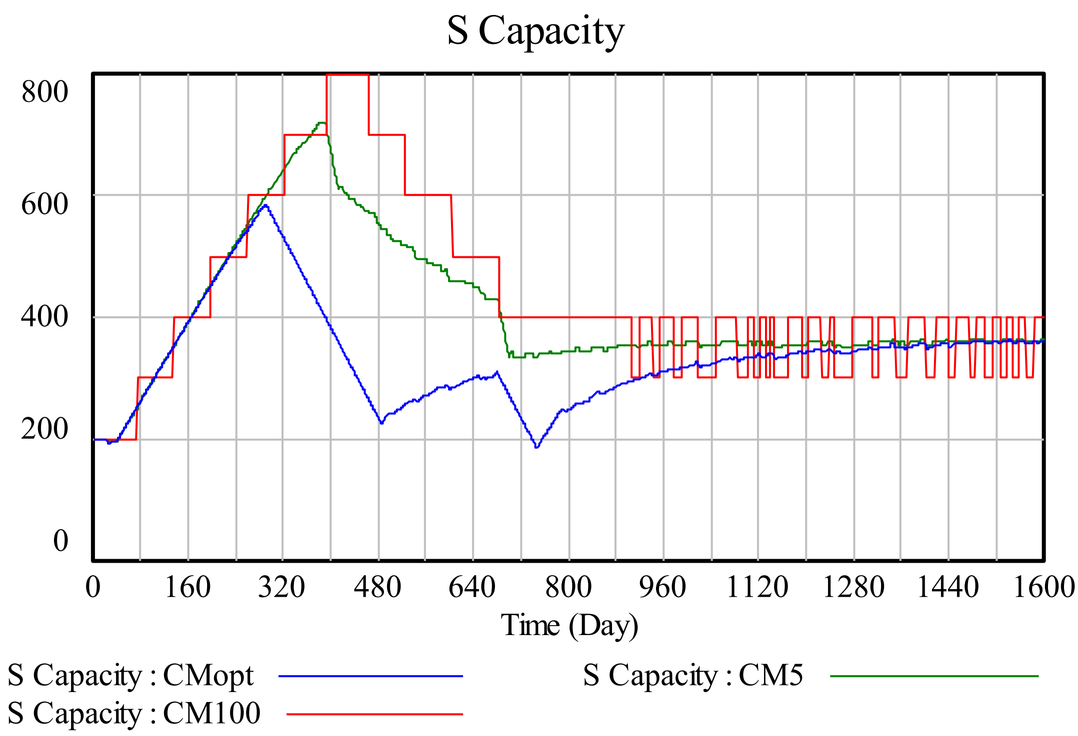
<그림 14-14> CM5, CM100, CMopt의 M Inventory(0-500일)



CMopt had the smallest vibration width and had a small whip effect. The largest oscillation width was for CM100. After 500 days, all three models showed stable shape.

S capacity was very different depending on the size of the chunk.

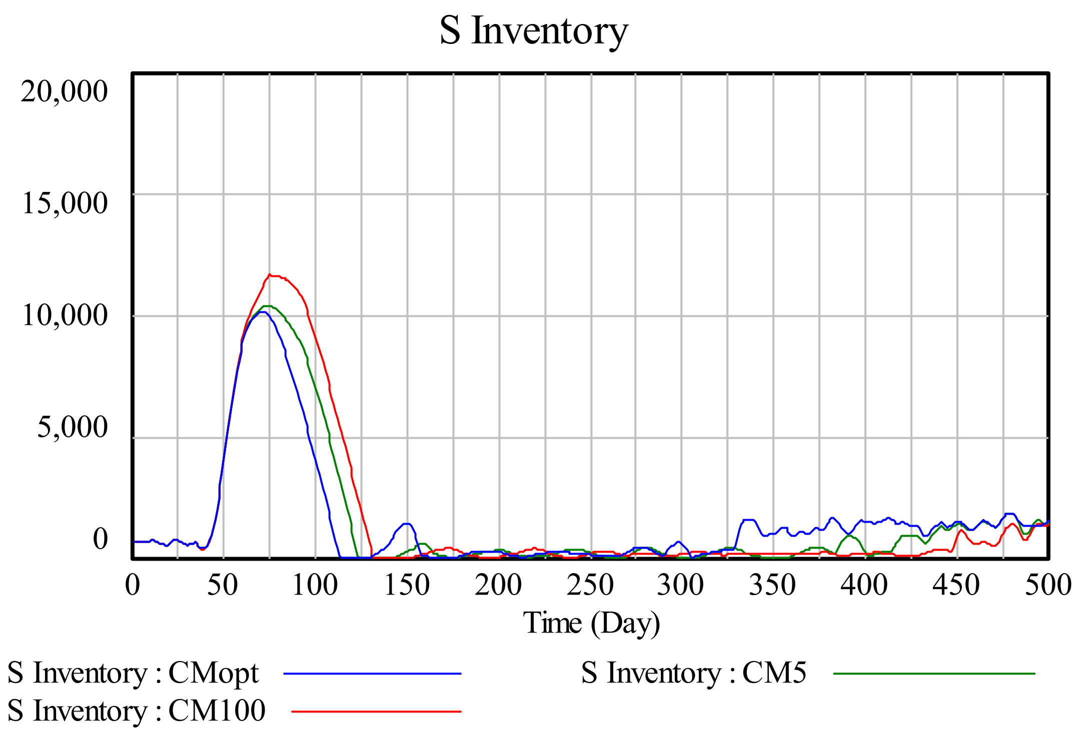
<그림 14-15> CM5, CM100, CMopt의 S Capacity



The minimum change size of C Mopt (the magnitude of the capacity extension) was found to be very small, about 2. It increases the number of transports up to approximately 300 days, after which a continuous decrease occurs. Then, after a few adjustments, it gradually finds a point of equilibrium. In the case of CM5, the size of the capacity expansion is larger than that of CMopt, so it increases and decreases slowly and quickly finds a balance point. In the case of the C M100, the balance point is found relatively quickly. Looking at the average number of units held, the CMopt has 333.80 units over the entire period, but the CM100 has 436.97 units, a difference of about 100 units. In the case of the CM5, it is 407.80, which is located between the two models.

The S Inventory according to S Capacity is shown in the following figure.

<그림 14-16> CM5, CM100, CMopt의 S Inventory(0-500일)



CMopt has the least whip effect and appears to be quick to defeat. On the other hand, CM100 has the greatest whip effect and appears to recover late. After 501 days, all three models showed a similar shape.

The performance for CM5, CM10, CM20, CM50, CM100, CMopt is as follows: Performance is in the following order: purchase cost, shortage cost, transportation cost, inventory cost, sales, and gross profit.

Table < 14-1> Performance Comparison by Size of Capacity Expansion

	Purchase Cost ($100)	Shortfall ($9)	Transportation cost ($100)	Inventory cost ($1)	Sales (USD)	Gross margin (USD)
CM5	19,979	96.73	59,842	3,100	395,935	200,339
CM10	19,979	99.73	59,841	3,101	395,935	200,500
CM20	19,979	96.01	59,842	3,108	395,935	199,588
CM50	19,979	104.28	59,841	3,104	395,935	201,087
CM100	19,979	153.77	59,842	3,135	395,935	196,059

CMopt	19,979	135.98	59,840	2,926	395,935	207,108

There was little difference between the purchase cost and the transportation cost. However, there was a slight difference in inventory costs and shortage costs. This difference determined the difference in gross profit.

If you include the cost according to the holding amount of the vehicle (capacity), there will be a clear difference, but the calculation may vary greatly depending on the vehicle holding method or depreciation method, so only the number of vehicles held is compared.

Table < 14-2> C apacity mean by magnitude of capacity expansion

	S Capacity	M Capacity	R Capacity	Total Capacity
CM5	407.80	362.17	355.78	1125.75
CM10	404.56	363.97	355.59	1124.12
CM20	412.95	364.19	356.05	1133.19
CM50	394.06	365.92	358.18	1118.16
CM100	436.97	367.70	362.96	1167.63
CMopt	333.80	361.98	362.27	1058.05

CM50 showed the least capacity, and CM100 was the largest. It is believed that this difference affected the inventory and shortfall. The total cost should be calculated by considering the cost of the ability to be possessed, and it should be applied differently depending on the situation of the industry or company.