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# ESTABLISHMENT OF PRODUCT OFFERING AND PRODUCTION LEVELING PRINCIPLES VIA SUPPLY CHAIN SIMULATION UNDER ORDER-TO-DELIVERY ENVIRONMENT

Shang-Tae Yee

Enterprise Systems Laboratory
General Motors Research and Development Center
30500 Mound Road
Warren, MI 48090, U.S.A.

## ABSTRACT

In support of the order-to-delivery (OTD) business initiative, a simulation framework has been developed at GM R&D. The OTD simulation program is aimed at simulating the behavior of the OTD supply chain using detailed inputs associated with demand, supply, and production processes. Customer demand variation is a key source of uncertainty in GM's supply chain. Early capture of customer demand fluctuation enables GM to effectively reduce aggregate mismatch between production and sales and appropriate time series models have been suggested to capture demand patterns based on actual data. The vehicle model and option mix with a given demand variation influences the performance of the OTD supply chain and provides a means to establish certain principles determining the extent of product offering and the scope of production leveling. Analyzing the impact of the model and option mix on primary supply chain performance measures, such as customer wait time, condition mismatch, and parts usage, capacitates reduction of the mismatch between demand and production and stabilizes supply chain operations.

## 1 INTRODUCTION

The order-to-delivery (OTD) is a new initiative of General Motors (GM) to deliver vehicles to customers with speed and reliability. In Costy and et al. (2000), the vision of the OTD is defined as "Personalized vehicles provided with zero customer inconvenience". Its challenge is to transform GM to a sense-and-respond enterprise focused on the customers. This transformation will have an effect on every activity related to GM, including suppliers, dealers, and customers. If we produce too many unpopular models, we must discount them with rebates or other incentives that cost GM a lot of money. Conversely, if we build too few hot sellers, we lose out on profit and customer preference. Build-to-order production avoids these problems by pulling through only the vehicles that customers want. The key objectives of the OTD business model are as follows:

- Order-to-delivery lead-time reduction between dealer/customer order and vehicle delivery.
- Order delivery date reliability improvement to provide dealer/customer with reliable delivery date at time of order.
- Real time customer experience by providing web enabled resources in terms of supply chain visibility.
- Supply chain constraints elimination to quickly sense and satisfy true market demand.

Under the OTD environment, customer demand triggers order movement to raw material supplier and manufacturer and then, initiates the movement of product to back down to the retailer. The customer demand drives production schedule and material procurement as well as scope and size of resources and capacity of supply and production processes. Randomness of customer demand patterns involves various behavior associated with economic status, new product introduction, competitor's business performance, etc. Accurate estimation of these demand patterns provides a key to disclose a big source of uncertainty of the GM supply chain. Model and option mix is one of the most critical drivers to affect the customer demand because it determines the extent of product choices the customers can take. Diversity in the model and option mix offers customers more choices, but results in more complexity in product development and production plan. Thus, the model and option mix steers the customer demand and determines the scale of product offering and the capacity of production leveling.

As mentioned in Winter (1997), customer preference for optional parts has been moving from simple electronic equipment (e.g., power windows, power mirrors, etc.) to more complicated electronically controlled units. Nowadays, the high-content vehicles are used as a mobile office in which various devices are installed to obtain real-time information, such as cellular phone, fax machine, navigation system, PDA, entertainment system, etc. It will be soon to see the state-of-the-art wireless communication devices mounted inside the vehicle. Drivers will be able to access Internet, to link office and home PC for file downloading, and to get services like map, direction, traffic congestion, smart highway information, etc. GM currently affords part of these services via the OnStar system.

Morgan and Daniels (2001) developed an integer programming-based technology adoption decision model that integrates the product mix with the technology adoption decisions. In their study, product mix and volume were recognized as important variables to determine cost effectiveness of new technologies. They considered market trend in which customer demand is increasing for sophisticated features of vehicles. The manufacturing firm's product mix is decided both by the set of products offered in the marketplace and the technology selected for the products. Setup and holding costs also affect the product mix and the technology choice decisions that maximize profits.

In addition, distribution strategy is influenced by the product mix at each plant because the extent of model and option combination determines the shipment volume of raw materials from suppliers to manufacturing plants and the finished vehicles from plants to different customer zones through a set of distribution centers. The model and option mix is associated with total fixed and variable costs subject to constraints imposed on demand, production capacity, warehouse capacity, raw material supply and requirements, and geography of customer zone outlets.

Understanding the impact of model and option mix on the supply chain performance brings in several benefits to GM. First, GM can align demand with supply by effectively steering customer needs toward product design and production plan. Next, GM can enable more stable production schedules by shaping necessary demand patterns. Also, GM can have operational stability by avoiding overtimes and short times, production shutdowns, and part shortages. The objective of this study is to establish fundamental guidelines for product offering and production leveling in terms of the model and option mix control by considering aggregate customer demand. This results in not only the enhancement of the customer satisfaction as to the extent of product choices, but also the better utilization of various resources and the production capacity. Given a particular demand pattern, we are interested in investigating the impact of the model and option mix on important supply chain performance measures, such as average customer wait time from the order placement to the vehicle delivery, condition mismatch, i.e., the difference between what the customers want and what they actually selected due to the unavailability of the desired model and options, and parts usage, i.e., the consumption level of optional parts that are needed for producing the given number of vehicles. Analyzing these performance metrics accordingly helps GM to better understand the behavior of its supply chain and to make appropriate strategic decisions. Because of sophisticated uncertainty in demand, supply, and production, simulation would be an only solution to analyze these performance measures as well as to answer other questions raised by the OTD initiative. Thus, we developed a simulation tool to model and analyze the OTD supply chain. The OTD supply chain simulation program includes the behavior of each supply chain link, namely, inbound logistics, manufacturing plants, outbound logistics, and dealers.

This paper is organized as follows. In Section 2, a brief description is presented for the OTD supply chain simulation program. In Section 3, simulation experiments are executed and their results are analyzed for three performance measures mentioned above. Finally, summary and conclusions are provided. The data in this study are disguised so as to avoid divulging information sensitive to GM.

## 2 OTD SUPPLY CHAIN SIMULATION

As an effort to answer the OTD issues, the OTD simulation team was organized, accommodating related cross-functional experts, to develop a simulation tool to model and analyze the OTD supply chain. In the past, there were several activities regarding supply chain simulation, such as evaluation of custom express delivery (CXD) outbound distribution network at GM R&D and strategic simulation effort called ASSIST at EDS/AT Kearney Europe. The CXD program is to deliver customer orders within 24 to 48 hours by truck delivery to reduce customer response time by holding popularly configured vehicles (PopCons) at regional distribution centers (Krishnan 2001).

GM R&D was responsible for developing a simulation framework, based on flexible and object-oriented concept, to quickly explore and evaluate innovative supply chain systems and processes with very detailed input data in support of OTD. The OTD simulation program processes its inputs associated with the uncertainty along customer demand, materials supply, and vehicle production. It is important to effectively generate the inputs for the simulation, which exhibit the best of real business environment. By adjusting the input parameters, we would like to identify the impact of the input changes on the performance of the OTD supply chain.

Microsoft (MS) Access is used as a front end user interface and all necessary initial input tables can be made as Access table format. Two Access Forms are provided to the user to specify the parameters for the simulation inputs generation and the simulation run. In the inputs generation Form, the user can specify the aggregate time series with related demand parameters, the model and option mix, and the production schedule. Also, the demand interval can be provided. In the simulation Form, the user exports the inputs obtained from the inputs generation module, runs the simulation, and imports the simulation outputs as Access tables. In addition, using the queries, various performance measures are created as Forms. Because of the important relationship of the simulation inputs with the model and option mix, we have more focus in explanation on the input generation than the simulation engine and the outputs.

## 2.1 Simulation Inputs Description

To simulate realistic behavior of a supply chain, the first step is to develop a mechanism providing the simulation inputs that mimic actual customer demand, materials supply, and vehicle production. Customer demand at aggregate level needs to be generated by reflecting past sales records. Each customer demand should include detailed configuration information as a customer places an order through a dealer with the requirement of a particular vehicle model and optional parts. On the production side, actual production schedules should be set up considering all shutdown days of a plant and for each valid production day, production capacity and parts availability should be generated. This section only describes some critical inputs, not all the inputs needed for the simulation. All required simulation inputs are created by the input generation module, written in C++, linked with the MS Access user interface, and stored as Access tables.

### 2.1.1 Aggregate Demand Generation

Aggregate customer demand can be produced using a time series model based on the past sales data. From another study (Yee 2002), it was found that GM's past sales data contain non-stationary behavior and seasonal patterns. The non-stationary behavior means that the time series exhibits wandering behavior with no fixed mean. The seasonal pattern indicates that similar effects repeat in a periodic manner. Two non-stationary models were recommended for representing aggregate demand; one is the integrated moving average (IMA) model of order (1,1) and the other is the seasonal IMA(1,1) model with year-to-year trend. Either model can be useful for producing the aggregate demand patterns with a small number of parameters (say, two or three).

### 2.1.2 Detailed Vehicle Configuration Generation

When a customer places an order, a particular vehicle type and a group of preferred optional parts are determined. One merchandizing model may contain ABS brakes with red exterior color, and the other merchandizing model may have ABS brakes and a sunroof with white exterior color and leather seat cover. When a wide variety of optional parts is given to the customer, the customer selection becomes extensive and product complexity increases a great deal accordingly. Currently, a single plant produces vehicles with a couple of hundred thousand configurations annually. There exists one tradeoff between the selection extent of optional parts and the product complexity. In addition, it is difficult to predict which optional parts the customer may select. The question is how to propose the model and option mix that is similar to actual selection of customers while satisfying their preference for the parts. This is very crucial because it determines how the plant enables to reduce product complexity with an appropriate model and option mix, levels the production schedule and capacity, and absorbs the customer's portfolio.

### 2.1.3 Production Schedule and Capacity Setup

In real production, constraints are primarily associated with production processes, material supply, and manpower. The production processes include manufacturing facility and equipment from individual machines, through production lines, to shop floor. The material needed to build a vehicle is supplied to the plant by suppliers. The availability of the parts, subassemblies, and assemblies is a crucial prerequisite for successful manufacturing. The work force actually controls and operates the plant utilizing these resources. The working hours with overtime and short time are established based on sales record, economic trend, etc. In this study, a production calendar is created taking into account three main production constraints mentioned above. It includes daily production capacity, part availability, and daily working hours. All shutdown days are reflected because no production happens during these dates. Even though daily production capacity might be the same, overtime and short time can be introduced to react to actual market demand. Whatever dates are given for the start and end of production, the production calendar is generated considering all shutdown days, including the weekends and holidays.

## 2.2 Simulation Engine Description

The simulation engine, written in C++, enables detailed and realistic analysis of complex OTD issues. It simulates production, distribution, and logistics systems and processes. The simulation objects consist of three types: structural objects, control objects, and event objects. The structural objects correspond to physical entities, such as supplier, manufacturer (plant), distributor (distribution center), retailer (dealership). Second, control objects represent control policies concerning supply, demand, and material flow. Last, event objects are related to the dynamic event occurrences of supply, demand, and material during the simulation. The simulation logic starts from getting a customer order and assigning it to the related location, i.e., dealership. The dealer sees if the ordered vehicle is deliverable in terms of the model and option mix. If the order is deliverable, then the dealer delivers the vehicle to the customer. Otherwise, the dealer looks for the ordered vehicle upstream and certain compromise may happen between the customer's desired configuration and the available configuration. If the customer compromises to purchase the best-matched vehicle moving between the plants and the dealership, the vehicle will be delivered to the customer. Otherwise, the dealer needs to place an order to the plant. From the plant perspective, based on the daily order from the dealerships, the plant sequences the customer orders considering the daily production capacity and schedules the material needed. The finished vehicles are transported through the logistic network to the dealerships. The simulation engine is linked with the MS Access simulation run Form that is used as an interface to feed the simulation inputs to the engine and to return the simulation outputs to the Access tables.

### 2.3 Simulation Outputs Description

Given a set of the simulation inputs, the simulation engine generates various outputs into Access tables, such as vehicle flow history, order flow history, and production history. From these output tables, using the queries, we provide several performance measures as Access Forms, namely, customer wait time, condition mismatch, parts usage counts, vehicle inventory, daily demand, daily sales, transit time, etc. Each performance measure is displayed as distribution and/or time series pattern. Similar to the simulation inputs, the simulation outputs are stored as the Access tables and necessary performance measures can be obtained using the queries.

## 3 SIMULATION EXPERIMENTS

One of the most important factors determining supply chain complexity is the number of merchandizing models and optional parts that indicate the scope and level of demand and production. The aim of simulation experiments is to identify the impact of the merchandizing model and optional part mix on supply chain performance. Among various performance measures, we focus on customer wait time, condition mismatch, and parts usage level. Because the top priority of the OTD is to reduce the OTD lead-time, we want to see what impact the model and option mix brings forth on the customer wait time. The condition mismatch implies the customer compromise that explains the change of customers' decision in the model and option mix of their order. The parts usage represents a good measure of the customer preference and enables to make the material replenishment plan ahead of time. Analyzing these performance measures mentioned above provides fundamental principles to offer product choices to the customer, to facilitate overall production leveling, and to reduce product complexity. In this sense, this analysis affords an opportunity to shape more profitable and appropriate vehicle model and option mix.

For the experiment purpose, the demand is generated for one year from Sept. 14, 1998 to Sept. 13, 1999. The IMA parameters generating the monthly demand include average daily units, white noise standard deviation, and moving average coefficient. In particular, the moving average coefficient acts as a drifting factor. It is known that industrial time series usually have moving average coefficient values between 0.6 to 0.8 and stock market has more volatility with much smaller values between 0.2 and 0.4 (Box and Luceno 1997). Figures 1 and 2 show the input demand generated by the moving average coefficient values of 0.7 and 0.3, respectively. Obviously, we can see that Figure 2 is more volatile than Figure 1. Both time series display non-stationary behavior and Figure 2 shows larger drift and amplitude than Figure 1.

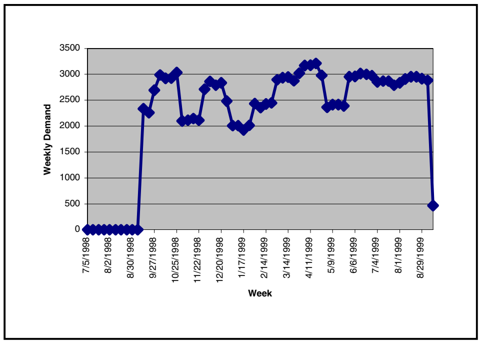


Figure 1: Aggregate Demand with Mov. Avg. Coef. 0.7

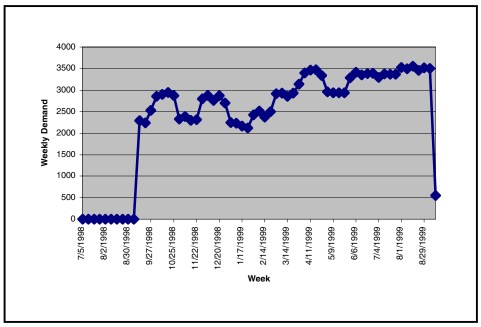


Figure 2: Aggregate Demand with Mov. Avg. Coef. 0.3

In the simulation experiments, a plant produces the vehicles from July 19, 1998 to July 3, 1999 for almost one year and relevant shutdown days are provided by considering all weekends and holidays. The production starts approximately two months earlier than demand onset. This intends to prepare some vehicle units (push portion) for allocating them to the dealers. After this initial period of production, actual customer order comes into the simulation process. The OTD simulation includes both push and pull production mechanism. When the daily demand is less than the daily production capacity, the plant push the rest of the capacity and assign the produced vehicles to certain dealers. If the daily demand is greater than the daily capacity, the remaining orders exceeding the capacity will be sequenced in the next available production day.

### 3.1 Customer Wait Time

By intuition, we can expect that the larger the number of merchandizing models is, the more complex the supply chain becomes and the longer the customer wait time is. We may want to see if a certain relationship exists between the number of merchandizing models and the average customer wait time for the given daily demand, daily production capacity, number of optional parts, etc. In this study, for the purpose of offering basic principles to construct the model and option mix plan, the number of merchandizing models and optional parts ranges from 1 to 64 and from 9 to 15, respectively. The number of merchandizing models was categorized into seven cases, such as, 1, 2, 4, 8, 16, 32, and 64. The eight-merchandizing model case was used as a baseline category with twelve optional parts. When a plant produces only one model, it is inflexible. When a plant produces sixty-four models, it has very high manufacturing flexibility. The total number of configurations is maintained as 32,768 units for each category. Making the number of merchandizing models twice decreases the number of optional parts by one.

#### 3.1.1 Equally Probable Merchandizing Models and Optional Parts

As a starting point, we consider the simplistic case in which each merchandizing model is equally probable with regard to demand and production. In addition, all optional parts are equally probable in which each part has the same penetration 0.5. This may not be happening in a realistic market, but it will provide us with a baseline to investigate the relationship between the number of merchandizing models and the customer wait time. When we have eight merchandizing models, each model has the same penetration 0.125 both in demand and production parameter setup. For all the seven categories, we performed sufficient replications and obtained the corresponding average customer wait times.

Figure 3 shows the relationship between the number of merchandizing models and the customer wait time for the aggregate demand pattern with the moving average coefficient 0.7. In Figure 3, the stock sales represent the vehicles that are already in the dealers' lot when the customers make transactions. Smaller moving average coefficient 0.3 produced higher average wait time and its standard deviation due to larger volatility. For the eight-merchandizing model case, the stock sales took 78 percent.

A relationship exists between the number of merchandizing models and the wait time. Varying the number of models from one to eight does not cause a vivid difference. The eight-merchandizing model case can be considered as a threshold because after that, the wait time increases very quickly. With the stock sales, the customer waits about 5 to 6 days to get the vehicle for the model range from one to eight. As the number of models goes beyond eight, the average wait time increases about five to six times because

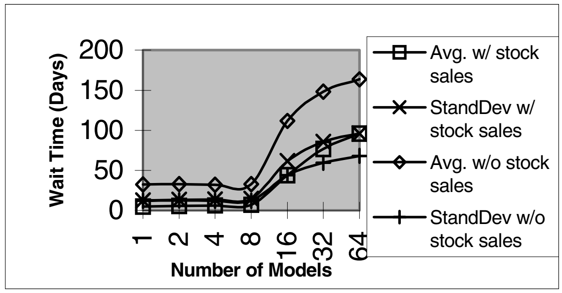


Figure 3: Number of Merchandizing Models vs. Customer Wait Time (with Moving Average Coefficient 0.7)

every customer placed the customized order based on the configuration preference. Without the stock sales, the average wait time is thirty days up to the model range of eight, but it increases four to five times when the number of models exceeds eight. It is concluded that the demand fluctuation did not seem to be a driver of the impact on the wait time and the number of models determines the time delay the customer needs to wait.

#### 3.1.2 Unequally Probable Merchandizing Models and Equally Probable Optional Parts

In a realistic market, the customer preference is biased to some merchandizing models. For example, much difference in sales can be found between high runners and low runners. The bias associated with the model preference can be realized by skewing certain percentage of the demand penetration to some of merchandizing models. In this section, we maintain the penetration of the optional parts as the same, that is, equally probable. Skewness is, in this study, given by the following rule. Skewness 1, 2, and 3 provide eighty percent of the total penetration to the half, the quarter, and the two-third of the merchandizing models, respectively. Table 1 shows three types of exponential skewness on the eight-merchandizing model category. The PDF and CDF in Table 1 denote probability density function and cumulative distribution function, respectively. For the skewness 1, 79.85 percent was actually given to the first half of the models. Skewness 2 assigns 80.21 percent on the first quarter of the models. Skewness 3 distributes 80.90 percent penetration to the first two-third of the models.

The skewnesses on merchandizing models did not affect the customer wait time. We can see that the customer wait time depends on the number of merchandizing models, not the model skewness.

#### 3.1.3 Unequally Probable Merchandizing Models and Optional Parts

We are also interested in the impact of the optional parts skewness on the correlation between the number of merchandizing models and the wait time. The skewness for the optional parts can be considered with or without the skewness of the models. Table 2 shows the skewness given to the optional parts. For the eight-merchandizing model case, skewness 1 (FS1) assigns the penetration 0.9 to the first half of the twelve optional parts, 0.5 to the next quarter of the parts, and 0.1 to the rest of the parts. Skewness 2 (FS2) allocates the penetration 0.9, 0.5, and 0.1 to the first quarter, the next half, and the remaining quarter of the optional parts, respectively. Skewness 3 (FS3) gives the penetration 0.9, 0.5, and 0.1 to the first three-fourth, the next 16.7%, and 8.8% of the optional parts, respectively. When the penetration becomes large for a particular part, the corresponding merchandizing model may have high probability to contain that part.

Table 1: Skewness of the Eight-merchandizing Model Case

| Skewness / Model No. | S1 | | S2 | | S3 | |
|---|---|---|---|---|---|---|
| | PDF | CDF | PDF | CDF | PDF | CDF |
| 1 | 0.3330 | 0.3330 | 0.5176 | 0.5176 | 0.1602 | 0.1602 |
| 2 | 0.2201 | 0.5531 | 0.2844 | 0.8021 | 0.1496 | 0.3098 |
| 3 | 0.1406 | 0.6937 | 0.1364 | 0.9385 | 0.1400 | 0.4498 |
| 4 | 0.1047 | 0.7985 | 0.0405 | 0.9791 | 0.1300 | 0.5799 |
| 5 | 0.0808 | 0.8793 | 0.0137 | 0.9929 | 0.1199 | 0.6999 |
| 6 | 0.0592 | 0.9385 | 0.0052 | 0.9981 | 0.1091 | 0.8090 |
| 7 | 0.0385 | 0.9771 | 0.0016 | 0.9997 | 0.0985 | 0.9076 |
| 8 | 0.0228 | 1 | 0.0002 | 1 | 0.0923 | 1 |

Table 2: Skewness of Optional Parts

| Skewness / Part No. | FS1 | FS2 | FS3 |
|---|---|---|---|
| 1 | 0.9 | 0.9 | 0.9 |
| 2 | 0.9 | 0.9 | 0.9 |
| 3 | 0.9 | 0.9 | 0.9 |
| 4 | 0.9 | 0.5 | 0.9 |
| 5 | 0.9 | 0.5 | 0.9 |
| 6 | 0.9 | 0.5 | 0.9 |
| 7 | 0.5 | 0.5 | 0.9 |
| 8 | 0.5 | 0.5 | 0.9 |
| 9 | 0.5 | 0.5 | 0.9 |
| 10 | 0.1 | 0.1 | 0.5 |
| 11 | 0.1 | 0.1 | 0.5 |
| 12 | 0.1 | 0.1 | 0.1 |

For the eight-merchandizing model case, Figure 4 illustrates the relationship between the skewness and the customer wait time. For the purpose of comparing the results, the fifteen skewnesses are presented in Figure 4 with the equally probable case mentioned in section A. The customer wait time is pretty smooth for various skewnesses, but the equally probable case EQ and the merchandizing skewnesses S1, S2, and S3 result in higher wait time with the stock sales. The average wait time of these four cases is 6.36 days. For the rest of skewness cases, the average wait time is 3.70 days. Intuitively, we can guess that EQ may result in higher wait time because it takes more delay in production setup and process. S3 generates highest wait time (6.73 days) since it is close to equally probable case in terms of penetration distribution as shown in Table 1. Relatively, S2 has the smallest wait time among these four

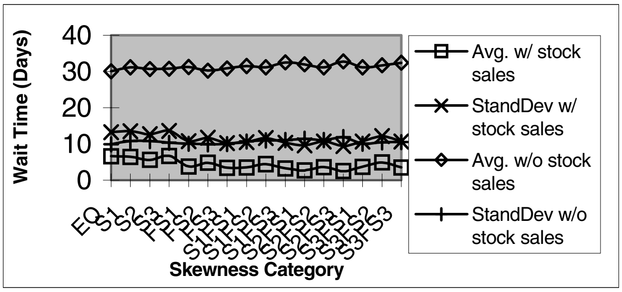


Figure 4: Skewness vs. Customer Wait Time

cases because its skewness is biased to a few models. The average wait time difference of 4.16 days exists between the maximum (6.73 for S3) and the minimum (2.57 for S2FS3). Similarly, the standard deviation difference of 4.19 days is found between the maximum (13.63 for S3) and the minimum (9.44 for S2FS3). An interesting thing is that the standard deviation and the average have the same pattern. Without the stock sales, the average wait time increases about five to ten times the stock sales case because all orders are customized. FS3 drives the increase of the wait time in all the combined skewness cases, such as S1FS3, S2FS3, and S3FS3. Because high penetration 0.9 is assigned to the three-fourth of the whole parts, more time may be needed in the assembly process.

### 3.2 Condition Mismatch

When a customer orders a vehicle in a dealer, the customer may have a preferred configuration with respect to the merchandizing model and the optional parts. The customer may or may not find a perfect match both in the model and the parts. The dealer makes an effort to locate the perfectly matched vehicle through the logistic network. In contrast, if the preferred vehicle is not available, the customer may compromise by eliminating or adding one or more optional parts to the configuration. Moreover, the customer may change the merchandizing model to another one. If the customer does not want to compromise, the dealer needs to place an order to the plant based on the required configuration. It would be meaningful to investigate the existence of a relationship between the number of merchandizing models and the condition mismatch with and without skewness on the models and the parts. The condition mismatch in a customer order can be represented by the number of conditions not matched with the preferred configuration.

#### 3.2.1 Equally Probable Merchandizing Models and Optional Parts

With equally probable demand assumption for the merchandizing models and the optional parts, Figure 5 shows the relationship between the number of merchandizing models and the condition mismatches, given the moving average coefficient 0.7. The eight-merchandizing model case appears as a threshold again. After that, the mismatch increases a lot, in particular, in the case of without-sold-orders. The sold orders mean the customized orders that are directly ordered to the plant. With sold orders, the condition mismatch decreases in every merchandizing model category because the customer preference is absorbed in the customized orders and there is less chance of mismatch. For the eight-merchandizing model case, the sold orders were 22 percent. Even in higher number of merchandizing models, such as thirty-two and sixty-four, the average mismatches are not quite bigger than those of fewer models. Up to the eight-merchandizing model, the mismatch difference between the with-sold-orders case and the without-sold-orders case is less than one. However, as the number of models is greater than eight, the mismatch difference becomes approximately three conditions. With the moving average coefficient 0.3, the average condition mismatch increases a little bit as we expected, but it is not significant. Hence, we would say that the demand fluctuation does not affect this correlation.

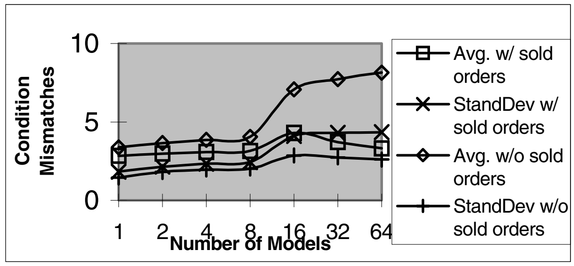


Figure 5: Number of Merchandizing Models vs. Condition Mismatch (Moving Average Coefficient 0.7)

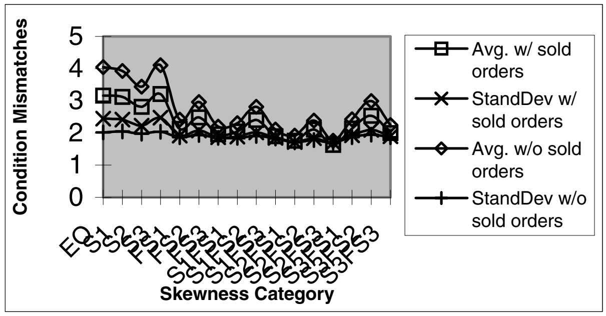


Figure 6: Skewness vs. Condition Mismatch

### 3.2.2 Unequally Probable Merchandizing Models and Equally Probable Optional Parts

With the skewnesses of Table 1 on the merchandizing models, the condition mismatch produced very similar pattern regardless of the presence of a skewness. The differences in the average mismatch values are negligibly small. We conclude that the skewness on the merchandizing models does not have any impact on the condition mismatch.

### 3.2.3 Unequally Probable Merchandizing Models and Optional Parts

In this section, the skewness is given both for the merchandizing models and the optional parts as mentioned in Tables 1 and 2. Figure 6 displays the relation between the skewness and the condition mismatch for the baseline case, i.e., the eight-merchandizing model with twelve optional parts. Intuitively, as we can guess that the sold orders absorb some extent of the mismatch, with-sold-orders case results in less average mismatch than without-sold-orders case. Both curves present pretty much the same pattern, but the standard deviation with sold orders has more variation than that of the without-sold-orders case. The equally probable case results in a very high average mismatch as we expected. In addition, the skewnesses on the models, namely, S1, S2, and S3, generate higher mismatch than the remaining skewed cases. With the sold orders, the average mismatch of these four cases, including EQ, is 3.08 conditions. For the rest of skewnesses, the average mismatch is 2.09 conditions. Without the sold orders, the average mismatches for higher and lower group are 3.88 and 2.38 conditions, respectively. The skewness S3 and S2FS3 result in the maximum and minimum average and standard deviation, respectively. The difference in the average mismatch between these two extreme skewnesses is 1.58 conditions in the case of including sold orders. For no sold orders case, the average difference is 2.35. Similar to the analysis result of the customer wait time, among three merchandizing skewnesses S1, S2, and S3, S2 generates the lowest mismatch because it skewed high penetration to the first quarter merchandizing models. In other words, we have less chance of mismatch since the customers are exposed to smaller number of choices of the models. In the same sense, as we can expect, S3 has a slightly higher value of the mismatch than S2 because it assigns high penetration to the first two-third of the merchandizing models. For the skewness of the optional parts, FS2 showed the largest mismatch because high penetration 0.9 is given only to the first quarter of the parts. In other words, because FS2 distributes the medium penetration 0.5 to the half of the optional parts, it has higher chance of mismatch. Conversely, it makes sense that FS3 has the smallest mismatch since it assigned the penetration 0.9 to the first three-fourth of the optional parts. When the skewness is considered both for the models and the parts, the skewness portion on the parts leads the overall mismatch. When the model skewness is combined with the part skewness, FS2 always results in the maximum mismatch regardless of any combination with the model skewness. Likewise, FS3 consistently causes the minimum mismatch in any group of combined skewness. Moreover, among three combined skewness groups, the second group (S2FS1, S2FS2, S2FS3) shows the smallest mismatch due to the influence of S2 that plays a role to reduce the mismatch. And in conclusion, the skewness on the merchandizing models is more critical to the condition mismatch than that on the optional parts.

### 3.3 Optional Parts Usage

Parts usage is a crucial enabler for establishing production and supply planning. Understanding the variation of the usage for each optional part drives the design of part buffer and the replenishment of each part. Keeping insufficient amount of parts in the plant may cause delay in production lead-time. Contrarily, sustaining too many parts may increase the inventory holding cost. Nowadays, many industries try to pursue the match of part demand-supply using certain types of visibility tools. Making the part usage visible from the plant workstation level to the suppliers may bring about the reduction of the customer wait time and the increase of productivity. Then, investigating the impact of the number of merchandizing models and the skewness on the part usage offers an opportunity to improve the part buffer design and to reduce the production lead-time.

#### 3.3.1 Parts Usage Variation with Number of Models

The number of merchandizing models may have an influence on parts usage under a given model skewness. Figure 7 demonstrates the part usage level by the number of merchandizing models with the skewness 1, while preserving the equal propensity of the optional parts. One particular observation is that as the number of models becomes greater, the part usage average decreases a little bit because the use of the parts disperses through all the models. However, the fluctuation increases due to the potential random bias coming from the bigger model space. In particular, the biggest variation is found in the sixty-four model case. The other skewnesses on the merchandizing models have resulted similar patterns in part usage (not shown).

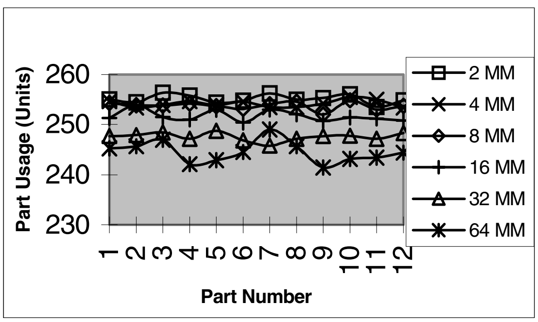


Figure 7: Part Usage Avg. Given Skewness 1

#### 3.3.2 Parts Usage Variation with Various Skewnesses

For the eight-merchandizing model case, several skewnesses are tested to investigate their impact on parts usage. Figure 8 displays the difference in the part usage average for different model skewnesses, while conserving the equal propensity of the parts. Obviously, we can see that giving some skewness on the models, whatever it is, results in less usage average than the equally probable case. We can easily guess that, in the equally probable case, every merchandizing model may consume the parts indifferently and then, the overall usage grows. Then, it generates higher usage average than any skewed case. However, among three skewness cases on the models, the skewness does not cause a big influence on the part usage, even though there exists slight difference. S1 has largest fluctuation in its average and standard deviation because it may provide the biggest room for random variation by assigning the penetration 0.8 to the first half models.

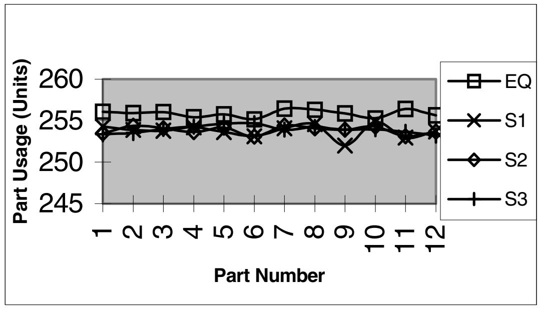


Figure 8: Part Usage Avg. with Different Model Skewnesses

Figure 9 shows the part usage outline with different skewnesses on the optional parts only. In this experiment, the model skewness is not considered, i.e., equally probable. The part usage curves in Figure 9 exactly remind us of the skewness assigned on the optional parts. Recall Table 2 that specifies each skewness for the optional parts. For example, FS1 has high consumption for the first half parts. Then, for the next quarter of the parts, the consumption takes the medium quantities. Last, for the last quarter of the parts, the consumption is low. Similarly, the usage patterns for the other two cases FS2 and FS3 are compatible to the input skewnesses of Table 2.

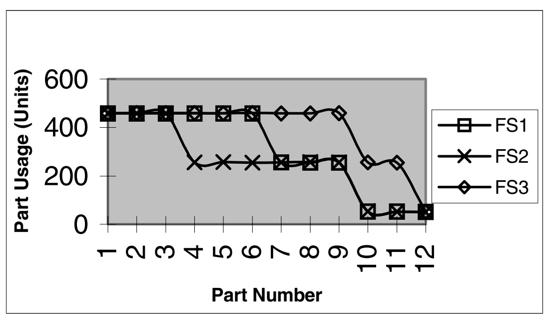


Figure 9: Part Usage Avg. with Different Part Skewnesses

Figure 10 shows the parts usage average, provided the combined skewness both on the models and the parts. Looking at Figure 10, it confirms the conclusion made just before about the impact of the model skewness on the part usage. In other words, the part usage patterns are pretty much the same whether the model skewness is added or not. For the other model skewness 2 and 3, very similar patterns are obtained (not shown). It is concluded that no clear evidence is found to explain the distinction based on the combined effect of the skewness.

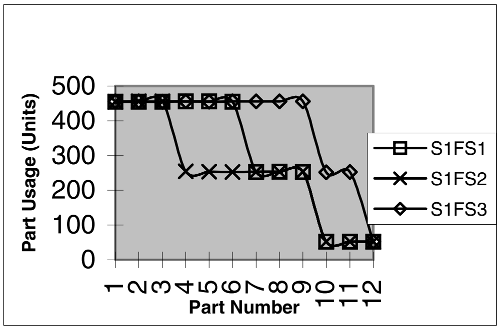


Figure 10: Part Usage Avg. with Combined Model Skewness 1

## 4 SUMMARY AND CONCLUSIONS

Using the OTD supply chain simulation program, simulation experiments have been performed to analyze the impact of the model and option mix on three important supply chain performance measures, namely, customer wait time, condition mismatch, and optional parts usage. The demand variation does not result in significant difference in the average wait time. The wait time increases quite a bit as the number of models is greater than eight. A threshold exists regarding the number of models, given a demand-production setup, including daily demand level, daily production capacity, number of models, and number of optional parts. Various skewnesses on the models and parts do not show any significant difference in the wait time. Condition mismatch has been analyzed to investigate the impact of demand fluctuation, number of models, and skewness. Similar to the customer wait time case, demand variation is not a driver to cause the mismatch. Without sold orders, the condition mismatch is higher than the with-sold-orders case because the customers just pick up the available vehicle in the dealer's lot and increases quickly when the number of models is larger than eight. The skewness on the models produces more mismatches in condition than that on the parts. As the number of models increases, the average of part usage decreases a little bit, but its fluctuation becomes bigger due to greater chance of discrepancy in optional parts distribution. Equally probable case generates higher usage average than any skewed one. When the skewness is given both on the models and parts, the resulting usage patterns resemble the skewness given in Table 2 and no clear skewness effect is found. From these analysis results, appropriate plan with regard to the number of models and optional parts can be developed to reduce customer wait time and condition mismatch. In addition, skewing penetration for certain optional parts can lower parts usage. With these principles proposed in this study, we can achieve better supply chain planning and execution.

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## AUTHOR BIOGRAPHY

**SHANG-TAE YEE** is a Research Engineer at the General Motor's Research and Development Center in Warren, Michigan in the US. He received his Ph.D. from Pennsylvania State University in 1998. His research interests are in supply chain simulation modeling and e-supply chain management. He is a member of INFORMS. His email address is <shang-tae.yee@gm.com>.