

Driving Service Excellence: A Hands-On Approach to Fill Rate Review and Corrective Action in Auto Manufacturing



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Abstract

Aim: This article aims to highlight the importance of fill rate as an important metric for after-sales performance in the automotive industry and equip manufacturers and service organizations with actionable methods to enhance inventory availability, strengthen customer trust, and build a more resilient after-sales ecosystem.

Methods: The article provides a framework for calculating fill rates using transactional data and demonstrates practical examples supported by data visualization developed in the Python programming language. It integrates data-driven analysis with operational insights to help diagnose poor fill rate performance, such as inaccurate demand forecasting, supplier delays, rapid changes in demand, material replenishment planning (MRP) parameter issues, and inventory mismanagement. It also outlines strategies to troubleshoot and improve them.

Results: The analysis shows how fill rate can reflect operational efficiency, supply chain agility, and customer-centric service delivery. By applying the calculation methods and visualizations, users can better understand inventory performance patterns, identify bottlenecks, and quantify the impact of the fill-rate variations on service operations and customer experience.

Conclusion: Fill rate is one of the most critical indicators in after-sales operations, as it directly influences vehicle downtime, customer satisfaction, brand loyalty, and long-term revenue growth. Ensuring consistently high fill rates demonstrates strong inventory management and operational effectiveness in an increasingly competitive automotive landscape.

Keywords: *Fill rate, material replenishment planning (MRP) parameters, reorder point (ROP), economic order quantity (EOQ), service level, back order (BO)*

1.0 INTRODUCTION

After-sales servicing has evolved into not only a crucial and significant revenue stream for auto manufacturers but also a strategic lever for customer retention, brand advocacy and long-term business growth. The global automotive aftermarket industry size was valued at USD 430.51 billion in 2024 and is projected to grow from USD 443.12 billion in 2025 to USD 565.73 billion by 2032, exhibiting a CAGR of 3.6%. North America continues to dominate the global market with a share of 31.34% in 2024 (*Automotive Aftermarket Industry Trends, Size Report, 2032*, 2025). Research indicates that high-quality servicing drives recurring business, strengthens brand loyalty, and differentiates manufacturers in a competitive market space (Salmeron et al., 2025). In a landscape where customers prioritize reliability and long-term support, after-sales operations directly contribute to the company's future sales growth.

However, ensuring service excellence heavily depends on operational efficiency and material availability. At both vehicle manufacturing and after-sales servicing, uninterrupted access to the right parts at the right time is essential to prevent downtime. This operational readiness is commonly assessed through the inventory fill rate, a key performance metric representing the percentage of customer orders fulfilled directly from the available stock without delay (Salmeron et al., 2025). Despite its simplicity, fill rate variability often masks deeper inefficiencies across demand forecasting, procurement, and inventory management. This raises an important research question: *How can transactional data be effectively leveraged to unmask the deeper inefficiencies and improve the inventory fill rate performance in after-sales operations?*

Addressing this question is critical for organizations aiming to develop and data-driven decision-making frameworks and enhance end-to-end supply chain visibility. In this article, I will propose a structured, data-centric approach for understanding and improving fill rate performance. Using synthetically generated datasets, I will demonstrate how the transactional data can be analyzed to measure fill rates, visualize performance trends, and identify root causes behind fill rate hits. The goal is to demonstrate how data-driven insights can reveal hidden inefficiencies and facilitate a more resilient and responsive after-sales supply chain.

2.0 WHAT ARE FILL RATES AND WHY DO THEY MATTER?

The fill rate is the percentage of customers' orders fulfilled from stock on hand in a given time frame. It measures the company's ability to fulfill customer orders from existing inventory. (Netstock, n.d.)

Fill Rate (%) = (Number of Order lines Filled/Total Number of Order lines) x 100

Although the fill rate formula appears simple, accurately calculating and measuring it in real-world after-sales operations is complex. It requires consolidation and processing of multiple data sources, such as inventory availability, supply lead times, and transactional fulfillment data, to derive a reliable fill rate. This complexity often leads to inconsistent measurement and incorrect performance interpretation, ultimately hindering organizations from making informed decisions to improve service levels.

Figure 1 illustrates a typical process flow for service center appointments, outlining key stages such as material allocation and parts ordering essential for completing each service. Every appointment generates a unique work order, serving as an internal reference and operational

backbone for the service activity. The work order captures a comprehensive set of details including vehicle information, service history, labor codes, parts allocation records, customer details, and technician notes ensuring full visibility into each repair or maintenance task. Select information from the work order is then used to create a Sales Order, which is shared with the customer to facilitate payment and invoicing.

As shown in Figure 1, the flow starts with checking the appointments. Service centers are expected to order or reserve the parts from in-stock available inventory for the scheduled appointments, if appointments fall within a week or any other standard timeframe set by the organization. There are exceptions for the vehicle on road (VOR) situations that need immediate attention. Once a vehicle arrives at the service center, technicians do the diagnosis and add or remove parts from the work orders. This is in addition to any parts ordered or reserved before for an appointment work order when it reached the standard appointment processing window. Sometimes, required parts may not be available within the company's network for an appointment and need to be ordered from a vendor, which is also known as a back order (BO) (Perez, 2025). If the vendor's lead time falls outside of the committed service completion date, then the customer needs to be informed of the revised schedule. Once the service is completed, the customer is informed about it to collect the vehicle. The work order is closed with the service completion and satisfactory handing over of the vehicle to the customer. This structured process ensures transparency, accuracy, and efficiency connecting technical execution with customer communication and financial accountability.

For the automotive industry, the average fill rate is 85% (Kpi Depot, n.d.). A lower fill rate indicates the need to evaluate the underlying factors influencing inventory performance, including but not limited to the reorder point (ROP), maximum stock level, economic order quantity (EOQ) (Fernando, 2025), and safety stock—collectively referred to as MRP parameters (Latham, 2023). Sometimes the lower fill rates are caused by supply constraints and abnormal demand spikes, which are considered as outliers that determine the MRP parameters. If the fill rate percentage exceeds 100%, then it indicates that the demand may have decreased or items are being simply ordered in excessive quantities, which calls for the need to change the ROP.

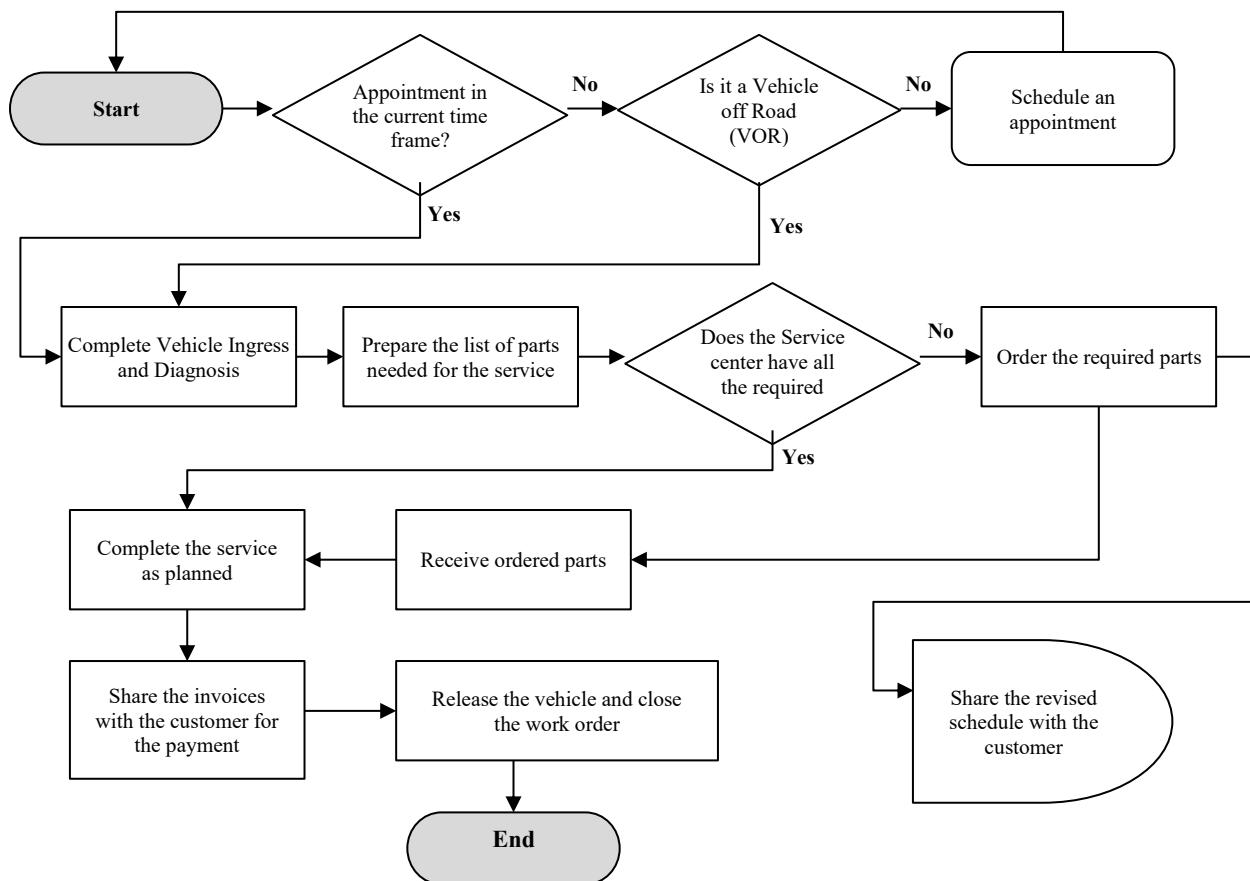


Figure 1: An Illustration Showing the Service Center Appointment Process Flow.

Source: Author

Let's try to understand the concept of fill rate and its consequences with an example below.

Example:

There is a service appointment for a vehicle. After diagnosis at the service center, the technician found that there would be a total of 10 parts that would require replacement. At that time, there were only 6 parts available in stock at the service center and the remaining 4 parts needed to be back-ordered by the service center. This will lead to a service center fill rate of 60% for my vehicle.

Fill Rate (%) = Number of Orders lines Filled/Total Number of Order lines) x 100

Fill Rate (%) = (6 /10) x 100 = 60%

In this situation, a customer will either have to take the vehicle home and come back after a few days or leave the vehicle at the service center, depending on the nature of the problem with the vehicle. In both cases, it's the customer ultimately who has to go through the inconvenience of the delay due to the unavailability of the parts at the service center. In addition to it, the unavailable items will be back-ordered, which will have a higher cost due to expedited shipment from the suppliers and a higher unit price for a lower quantity to fulfill the work-in-progress appointments.

2.1 Fill Rate and Service Level

The service level is the probability of filling customer demand during an order cycle from the on-hand inventory (Sapra, 2021). If the company's service rate for an item is 90%, it can fill orders 90% of the time for the same item. 10% of the time, it will run into shortages.

In general, a high fill rate often leads to high service levels as customers receive the goods as they require them. With higher demand fluctuation and longer replenishment lead times, businesses plan for large inventories to support high service levels, which increases inventory holding costs. There is a threshold after which the service level improves marginally while the costs of maintaining inventory increase drastically (Cheng et al., n.d., #). This requires detailed analysis to find an inventory level that balances holding costs with the benefits of high service levels. Business objectives often drive service levels.

3.0 FILL RATE ANALYSIS

Fill rate analysis is a critical process for identifying underlying causes of service performance issues and implementing preventive measures for subsequent operational cycles. While such analysis is commonly performed every week, its frequency may be adjusted to daily or at other intervals based on organizational requirements and data availability.

A weekly fill rate analysis provides a robust dataset for monitoring trends over time and comparing current performance against previous periods for a given service center. It facilitates the identification of components that have experienced recurrent fill rate hits, both within a specific service center and across the service center network. Moreover, weekly data supports management reporting and enables informed, cross-functional decision-making, such as diagnosing supply–demand imbalances, delayed replenishments from suppliers or distribution centers, logistics bottlenecks, and seasonal or regional variations influencing component failure rates.

Conversely, a daily fill rate analysis is primarily utilized for the early detection of anomalies or outliers in stock-keeping unit (SKU) ordering patterns. Conducting this analysis at a higher frequency allows for prompt corrective actions, thereby mitigating potential service disruptions before the completion of the weekly reporting cycle. For fill rate analysis, a typical end-to-end process flow can be represented as shown in Figure 2.

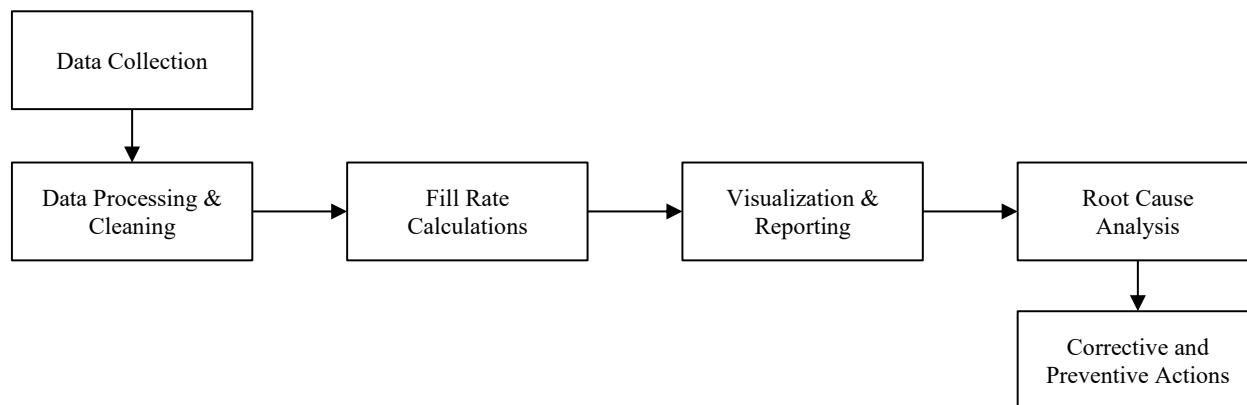


Figure 2: An Illustration Showing the Fill Rate Analysis Process Flow.

Source: Author

3.1 Data Collection

For the Fill rate analysis for a given time frame, it is necessary to extract service center-level data corresponding to the order lines linked with the work orders of scheduled appointments in the same time frame. Each part, in addition to a work order, along with its required quantity, generates a distinct order line.

Work order data are collected from service centers at defined intervals and stored either on cloud-based platforms or local servers. It is advisable to maintain historical data for future reference and trend analysis; this often necessitates the use of cloud storage solutions to overcome potential data capacity limitations. Work order data are collected from service centers at defined intervals and stored either on cloud-based platforms or local servers. It is advisable to maintain historical data for future reference and trend analysis; this often necessitates the use of cloud storage solutions to overcome potential data capacity limitations. The extracted data typically exists in raw form and may require preprocessing or data preparation before performing fill rate calculations.

Key data elements required for fill rate analysis include the following;

Work Order (WO) is an appointment-level umbrella that groups one or more service requests for a visit. Service requests inside the work order carry the specific labor codes and parts that roll up to the estimate/invoice. It is a unique number assigned to a customer appointment. It is referenced for any internal transactions and references. Any required labor codes or service requests are added to the work order for completing the service. Customer authorization happens at the WO level.

Service Request (SR) is a comprehensive record that captures all key details related to a customer's service interaction. It includes the customer's concern, selected payment mode, service scheduling information, parts and labor line items, start and end date/time of the service, and the current status. The SR serves as a single point of reference for tracking, managing, and resolving customer service activities efficiently.

Labor Code (LC) is a standardized code that defines a technician's task or operation associated with a specific model or system, along with a predefined labor time. Each labor code represents a distinct service activity—such as diagnosis, replacement, adjustment, calibration, or inspection—and determines the corresponding labor time and pricing on the service request (SR). Labor codes generally reside within the SR (not directly on the work order) and appear on the customer's repair order or invoice, driving accurate time tracking, billing, and warranty cost accounting.

3.2 Data Preparation

For the weekly fill rate calculations, data should be aggregated every week according to appointment schedules and presented in a tabular format, including the appointment date, work order (WO), part number, part status, order date (if ordered) and quantity of each part. Each distinct row in the table will represent an order line. In cases where the required part is available at the service center for the designated WO within the reference week, the entry will be classified as "Filled." On the other hand, if the part is not available, it will be placed on order and designated as "No Fill." Table 1 provides an overview of the core dataset that serves as the foundation for fill rate analysis and reporting.

Table 1: Sample Data for Fill Rate Calculations (Synthetic Data Generated Using Python Programming)

	Appointment Date	Work Order (WO)	Part Number	Part Status	Quantity	Service Center	Vehicle Model	Part Family	Fill Status	Week No.
0	2025-10-01	WO10925	PN-8531	Available	4	Dallas	Model A	Non Hardware	Filled	39
1	2025-10-01	WO11808	PN-9502	Available	4	Dallas	Model B	Non Hardware	Filled	39
2	2025-10-01	WO11340	PN-9199	Available	1	New York	Model B	Non Hardware	Filled	39
3	2025-10-01	WO11792	PN-6209	Available	3	New York	Model B	Hardware	Filled	39
4	2025-10-01	WO11778	PN-9932	Available	2	New York	Model A	Hardware	Filled	39
5	2025-10-01	WO10108	PN-6808	Available	5	Ohio	Model C	Non Hardware	Filled	39
6	2025-10-01	WO10249	PN-2279	Available	2	Hayward	Model A	Hardware	Filled	39
7	2025-10-01	WO12734	PN-6851	Available	3	New York	Model A	Non Hardware	Filled	39
8	2025-10-01	WO12445	PN-2436	Available	3	Miami	Model A	Hardware	Filled	39
9	2025-10-01	WO12720	PN-9239	Available	3	Dallas	Model C	Tires	Filled	39
10	2025-10-01	WO12717	PN-6849	Not Available	2	Ohio	Model A	Non Hardware	No Fill	39
11	2025-10-01	WO11756	PN-6530	Available	5	Ohio	Model A	Hardware	Filled	39
12	2025-10-01	WO12696	PN-6851	Available	1	Miami	Model B	Tires	Filled	39
13	2025-10-01	WO11723	PN-9673	Available	3	New York	Model C	Hardware	Filled	39
14	2025-10-01	WO12690	PN-1103	Available	5	Ohio	Model A	Hardware	Filled	39
15	2025-10-01	WO12448	PN-5857	Available	4	Phoenix	Model C	Non Hardware	Filled	39

The following additional data can be incorporated to support further analysis:

3.2.1 Do not stock parts (DNS)

Vehicle identification number (VIN) specific parts must be identified and categorized, as they are unique to individual vehicles and are not intended for stocking at service centers. It is therefore acceptable to incur fill rate impacts for these components. Examples of VIN-specific parts include physical keys, vehicle control modules (VCMs), battery packs for electric vehicles (EVs), axle modules (AXM), and similar items. These parts should be classified as ‘Do Not Stock’ (DNS) to reflect their specialized nature and low likelihood of reuse across vehicles. It’s good to have a dynamic list of such parts and should be used to flag such parts in fill rate reviews for clarity.

3.2.2 Order frequency

Order frequency may be daily, weekly, bi-weekly, monthly, or quarterly, depending on the historical consumption patterns of each part. It is advisable to determine the appropriate order frequency both at the individual service center level and across the entire service center network. This approach helps in identifying localized as well as network-wide trends. There may also be instances where the order frequency for a specific service center differs from that established at the network level.

Excel and Google Sheets can quickly reach their row or file size limits when working with large datasets. In such cases, Python provides a more efficient and scalable solution for data analysis. In practical applications, data is often retrieved from cloud-based or local servers using SQL queries. SQL queries can be easily integrated within Python scripts to extract data directly from databases for further processing and analysis. The Python code below demonstrates the order frequency classification. In this example, ‘df’ refers to the DataFrame created for this article. If you plan to

use this code, replace 'df' and the column names with those from your own dataset. Table 2 shows the output generated by the code.

-----# SERVICE CENTER CONSUMPTION FREQUENCY

```
df_center_freq = (  
    df.groupby(["Service Center", "Part Number"])["Appointment Date"]  
    .apply(lambda x: x.sort_values().diff().dt.days.mean())  
    .reset_index(name="avg_gap_center")  
)  
df_center_freq[["Service Center", "Frequency"]]  
df_center_freq["avg_gap_center"].apply(classify_frequency)
```

```
# Drop any existing frequency columns before merge to avoid _x/_y
df = df.drop(columns=["Service Center Frequency", "Network Frequency"], errors="ignore")
# Merge Service Center Frequency
df = df.merge(
    df_center_freq[["Service Center", "Part Number", "Service Center Frequency"]],
    on=["Service Center", "Part Number"],
    how="left"
)
```

NETWORK CONSUMPTION FREQUENCY (mode across centers)

```
df_network_freq = (  
    df_center_freq.groupby("Part Number")["Service Center Frequency"]  
    .agg(lambda x: x.mode().iloc[0] if not x.mode().empty else "Quarterly")  
    .reset_index(name="Network Frequency")  
)
```

Merge Network Frequency

`df = df.merge(df_network_freq, on="Part Number", how="left")`

Final cleanup and sort

`df = df.sort_values(by="Appointment Date").reset_index(drop=True)`

Table 2: Data With Service Center and Network Consumption Frequency Classification

Appointment Date	Work Order (WO)	Part Number	Part Status	Quantity	Service Center	Vehicle Model	Part Family	Fill Status	Week No.	Service Center Consumption	Network Consumption
2025-10-02	WO12580	PN-9774	Available	3	Dallas	Model C	Hardware	Filled	39	Weekly	More than Monthly
2025-10-02	WO12879	PN-3802	Available	5	Ohio	Model B	Tires	Filled	39	More than Monthly	Daily
2025-10-03	WO12995	PN-5054	Available	2	Hayward	Model C	Hardware	Filled	39	Weekly	More than Monthly
2025-10-04	WO11414	PN-6713	Not Available	3	Ohio	Model B	Hardware	No Fill	39	Weekly	More than Monthly
2025-10-05	WO12791	PN-5484	Available	5	Ohio	Model C	Non Hardware	Filled	40	Weekly	More than Monthly
2025-10-06	WO12086	PN-7304	Not Available	5	Miami	Model C	Hardware	No Fill	40	More than Monthly	Bi-weekly
2025-10-07	WO10947	PN-3823	Not Available	2	Phoenix	Model B	Non Hardware	No Fill	40	Weekly	More than Monthly
2025-10-07	WO12888	PN-3512	Available	1	Phoenix	Model B	Hardware	Filled	40	More than Monthly	Bi-weekly
2025-10-07	WO11503	PN-1264	Not Available	4	Phoenix	Model A	Hardware	No Fill	40	More than Monthly	Bi-weekly

3.2.3 Material replenishment planning (MRP) parameters

MRP parameters, such as the Reorder Point (ROP), EOQ, rounding value, and maximum stock levels, are generally updated weekly. These updates should be incorporated into the analysis to identify SKUs that may require parameter adjustments to align with recent consumption patterns.

3.2.4 Unrestricted stock

Available stock at service centers helps determine if manual stocking is needed beyond automated replenishment. Including warehouse and distribution center stock further aids in deciding whether a specific SKU should be sourced from an alternate location or backordered.

3.2.5 Last 4 weeks consumption

The consumption data from the previous four weeks for a specific SKU can help fine-tune MRP parameters when necessary. Since MRP settings rely heavily on historical consumption trends, they may respond slowly to sudden demand changes, leading to potential lags in parameter adjustment.

3.2.6 Classification parts by size

Classifying parts by size supports the evaluation of replenishment quantities. Larger parts generally warrant smaller replenishments, whereas smaller parts can be stocked in greater

quantities to minimize shipment frequency and logistics costs. MRP parameters for individual service centers can then be refined accordingly when reviewing fill rate performance.

After incorporating the additional data, the updated fill rate analysis table appears as shown below in Table 3.

Table 3: Data Table Showing Part Classification by Part Size and Part Family Grouping.

Appointment Date	Week No.	Service Center	Part Number	Vehicle Model	No Fill Count	Quantity	Service Center Consumption	Network Consumption	ROP	Max Stock	EOQ	Last 4 Week Consumption	Unrestricted Stock	Part Size	Part Family
2025-10-02	39	Miami	PN-2191	Model A	1	3	More than Monthly	Monthly	78	99	122	59	2536	Large	Hardware
2025-10-05	40	Dallas	PN-7512	Model C	1	3	More than Monthly	Bi-weekly	22	49	127	9	2652	Large	Non Hardware
2025-10-08	40	Miami	PN-8645	Model C	1	2	Weekly	More than Monthly	12	41	48	19	1236	Tiny	Tires
2025-10-14	41	Miami	PN-8645	Model C	1	5	Weekly	More than Monthly	29	41	79	83	2747	Large	Tires

3.3 Fill Rate Reporting

Fill rate (FR) is measured at the various levels. The most common ones are at the network and service center level. Fill rates can also be determined at the vehicle variant, order frequency and part family level.

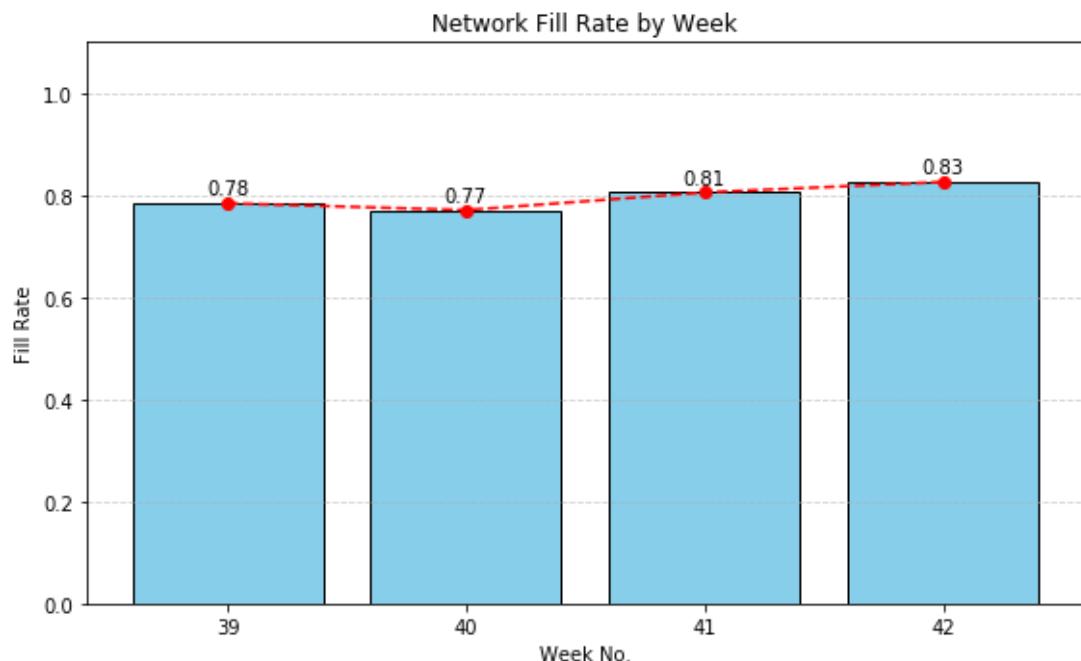


Figure 3: Bar Chart Showing Fill Rate from Week 39 To Week 42 With Trend Line.

Source: Author

Figure 3 illustrates the variation in fill rates, ranging from 78% to 83% across Weeks 39 to 42. The metric was computed by aggregating records according to the 'Fill Status,' utilizing the Python script presented below. Furthermore, a baseline reference line may be incorporated into the graph to contextualize fill rate performance relative to the established benchmark. As per the figure, the

fill rate exhibited a noticeable drop in week 40, followed by steady recovery over the next two weeks.

Import Libraries

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Load dataset

```
df = pd.read_excel("synthetic_service_data.xlsx")
```

Ensure Week No. is integer

```
df["Week No."] = df["Week No."].astype(int)
```

Network Fill Rate by Week

```
weekly_summary = df.groupby("Week No.").agg(
    total_orders=("Work Order (WO)", "count"),
    filled=("Fill Status", lambda x: (x == "Filled").sum())
).reset_index()
weekly_summary["Fill Rate"] = weekly_summary["filled"] / weekly_summary["total_orders"]
```

```
plt.figure(figsize=(8,5))
bars = plt.bar(weekly_summary["Week No."], weekly_summary["Fill Rate"], color="skyblue",
edgecolor="black")
```

Add values on top

for bar, rate in zip(bars, weekly_summary["Fill Rate"]):

 plt.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.01, f'{rate:.2f}', ha="center", va="bottom")

Trend line

plt.plot(weekly_summary["Week No."], weekly_summary["Fill Rate"], color="red", marker="o", linestyle="--")

plt.xlabel("Week No.")

plt.ylabel("Fill Rate")

plt.title("Network Fill Rate by Week")

plt.xticks(sorted(df["Week No."].unique()))

plt.ylim(0, 1.1)

plt.grid(axis="y", linestyle="--", alpha=0.6)

plt.tight_layout()

plt.show()

Service center reviews conducted at the company or network level help identify macro-level issues such as demand surges for specific items, seasonal field trends, new part additions to the Service Bill of Materials (SBOM), part quality issues, and supply chain disruptions.

Table 4: Service Center Fill Rate by Weeks

Week No.	39	40	41	42
Service Center				
Dallas	0.793103	0.775148	0.828402	0.792208
Hayward	0.712500	0.830303	0.823529	0.797297
Miami	0.873874	0.742515	0.808989	0.857143
New York	0.764045	0.744966	0.784530	0.833333
Ohio	0.772727	0.737430	0.796178	0.845238
Phoenix	0.756410	0.795181	0.787671	0.833333

Table 5: The Count of Filled Service Orders and Total Orders By Weeks

Service Center	Filled Order Lines_Week_40	Filled Order Lines_Week_41	Filled Order Lines_Week_42	Filled Order Lines_Week_43	Total Order Lines_Week_40	Total Order Lines_Week_41	Total Order Lines_Week_42	Total Order Lines_Week_43
Dallas	85	106	140	34	105	145	163	41
Hayward	112	147	170	38	132	189	201	48
Miami	99	137	154	33	125	172	180	49
New York	86	112	157	32	101	149	190	40
Ohio	103	136	143	39	130	171	173	45
Phoenix	88	125	124	22	108	151	160	32

Table 4 illustrates the weekly fill rates across service centers. These rates are calculated by aggregating the Fill Status data for each service center using the Python code shown below. This table provides a clear view of fill rate performance and allows easy comparison of trends across service centers over time. An additional view, shown in Table 5, displays the total order lines by service center, offering insights into workload levels and order fulfillment performance across weeks.

2. Service Center Fill Rate by Week Table

```
service_center_summary = df.groupby(["Service Center", "Week No."]).agg(
    total_orders=("Work Order (WO)", "count"),
    filled=("Fill Status", lambda x: (x == "Filled").sum())).reset_index()
service_center_summary["Fill Rate"] = service_center_summary["filled"] /
service_center_summary["total_orders"]
```

Pivot table: Service Center as rows, Week No. as columns

```
service_center_pivot = service_center_summary.pivot(index="Service Center", columns="Week No.", values="Fill Rate")
```

Individual service center fill rate analysis highlights the issues related to MRP parameters, stock discrepancies, internal network distribution inefficiencies or any local trend or challenges that need to be addressed differently. Fill rate analysis can be further deep dived into identifying the fill rate performances by other attributes like fill rate by vehicle model or fill rate by part family and so on, based on the business requirement.

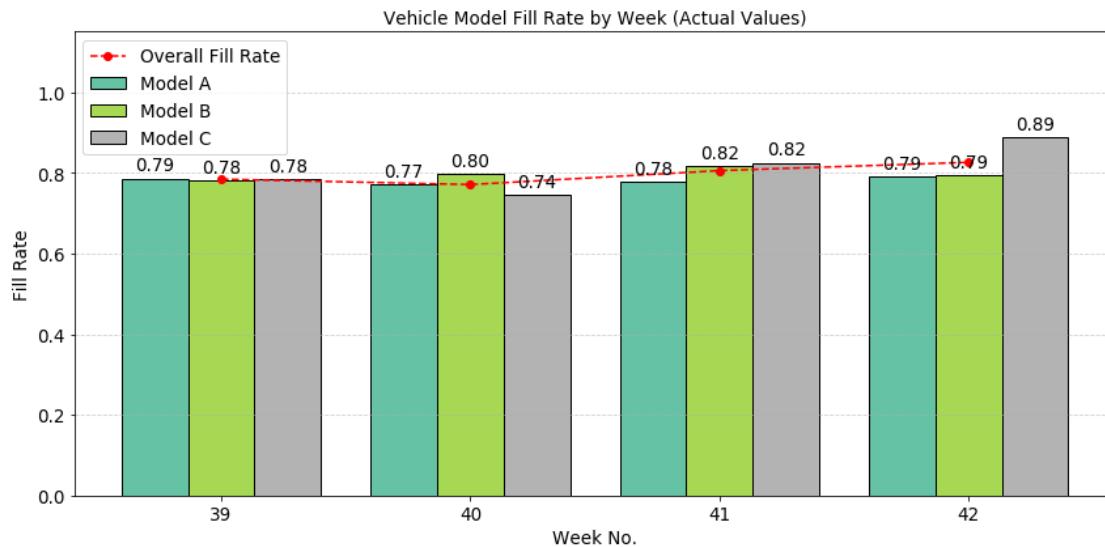


Figure 4: Bar Chart Showing Fill Rate by Vehicle Model from Week 39 To Week 42 With Trend Line.

Source: Author

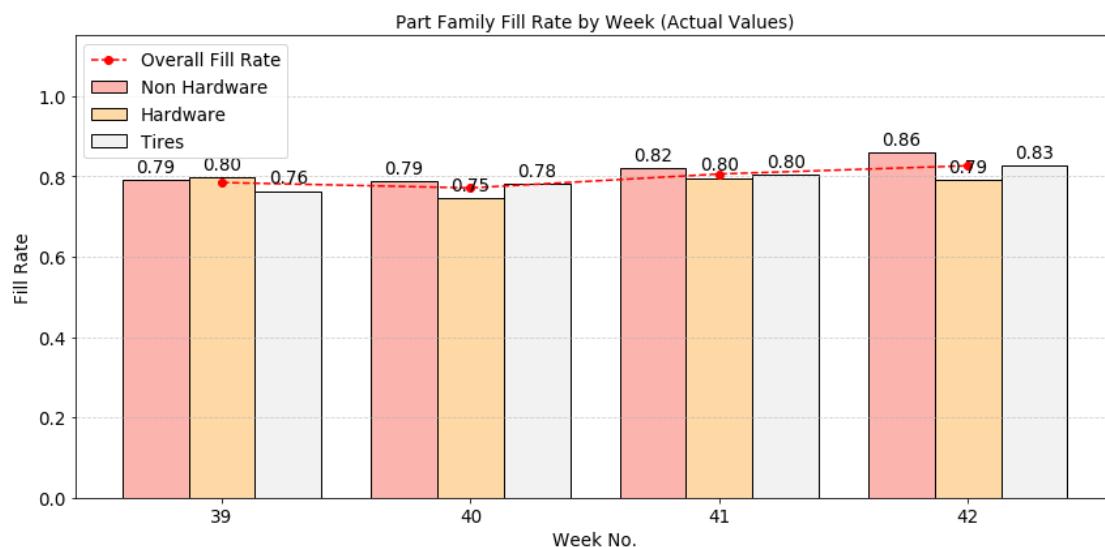


Figure 5: Bar Chart Showing Fill Rate by Part Family from Week 39 To Week 42 With Trend Line.

Source: Author

Figure 4 illustrates the weekly variation in fill rates across different vehicle models, derived by aggregating the Fill Status data by both week and vehicle model. This view helps in identifying model-specific supply or fulfillment challenges over time. In contrast, Figure 5 presents the network-level fill rate trends by part family, enabling quick identification of part categories that may require further investigation or corrective action. The Python code provided below can be easily adapted to generate similar visualizations — such as Figures 4 and 5 — by modifying the aggregation logic to group by any desired column or attribute.

Review related to the part, Model variants, order frequency, and part family helps in identifying any problematic areas related to design, manufacturing quality and supplier capability and capacity risks. Parts with higher and consistent order frequency are supposed to have the least fill rate hits, as such items will generally have steady and reliable forecasts. Each company has different ways to group the parts based on certain logical criteria, such as hardware/fastener and non-hardware, wheel and Tires, windshields, batteries, accessories, etc.

Vehicle Model Bar Chart with Annotations

```
width = 0.8 / len(vehicle_models) # small offset for each category
plt.figure(figsize=(12,6))
colors_vm = plt.cm.Set2(np.linspace(0,1,len(vehicle_models)))
```

For *i*, *vm* in enumerate(vehicle_models):

```
    vm_data = df[df["Vehicle Model"]==vm].groupby("Week No.").agg(
        total_orders=("Work Order (WO)", "count"),
        filled=("Fill Status", lambda x: (x=="Filled").sum())
    )
    vm_data["Fill Rate"] = vm_data["filled"]/vm_data["total_orders"]
    rates = vm_data["Fill Rate"].reindex(weeks, fill_value=0)
    bars = plt.bar(x + i*width, rates, width=width, color=colors_vm[i], edgecolor="black",
    label=vm)
```

Annotate each bar

```
for bar, rate in zip(bars, rates):
    plt.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.01, f'{rate:.2f}',
    ha='center', va='bottom', fontsize=fontsize)
```

Trend line

```
plt.plot(x + width*(len(vehicle_models)-1)/2, overall_weekly["Fill Rate"], color="red",
marker="o", linestyle="--", label="Overall Fill Rate")
```

```
plt.xlabel("Week No.", fontsize=fontsize)
plt.ylabel("Fill Rate", fontsize=fontsize)
plt.title("Vehicle Model Fill Rate by Week (Actual Values)", fontsize=fontsize)
plt.xticks(x + width*(len(vehicle_models)-1)/2, weeks, fontsize=fontsize)
plt.yticks(fontsize=fontsize)
plt.ylim(0, 1.15)
plt.grid(axis="y", linestyle="--", alpha=0.6)
plt.legend(fontsize=fontsize)
plt.tight_layout()
plt.show()
```

4.0 FILL RATE REVIEW AND ACTIONS

The primary objective of a fill rate review is to identify underlying issues that contribute to missed fill rate and to implement corrective measures that prevent their recurrence in future cycles. This process requires analysts to collect supplementary data to conduct a comprehensive root-cause analysis of each fill rate deviation. Figure 6 shows a sample fill rate process flow that can be used for identifying some of the root causes for the fill rate misses. In most cases, material replenishment is assumed to be automated for the majority of parts within scope. Manual replenishment, particularly for products with complex Bills of Materials (BOMs) such as those used in the automotive sector, is inefficient, labor-intensive, and not scalable.

The analysis typically begins by verifying whether Material Requirements Planning (MRP) parameters are active for the service center experiencing a fill rate shortfall. If MRP is active, the next step is to examine whether forecasts for upcoming weeks are available and sufficient based on recent consumption trends. This step is crucial, as Maintenance, Repair, and Operations (MRO) planning often relies heavily on historical consumption data. When such data is incomplete or when consumption patterns are irregular, the root causes of fill rate issues may be overlooked. In these cases, MRP parameters may require fine-tuning based on feedback from service centers. However, if the deviation results from a temporary or one-time demand surge, parameter adjustments may not be necessary.

In certain situations, parts may be physically available at service centers, yet fill rate hits still occur. This often happens when the service center team fails to recognize incoming or newly received stock. Such cases should be promptly addressed by engaging with the respective service centers to ensure awareness and timely stock utilization. Implementing and actively using parts tracking dashboards can be highly effective in identifying and minimizing these instances. MRP systems cannot trigger automatic replenishments if adequate stock levels are not available. For parts contributing to fill rate shortfalls, it is essential to explore opportunities for restocking from alternative distribution centers or by reallocating surplus inventory. These situations often highlight broader demand-supply imbalances, which may arise from supplier capacity constraints,

sudden forecast increases requiring additional production, or quality issues leading to material returns. In such cases, maintaining optimal inventory levels at service centers becomes challenging due to limited supply availability.

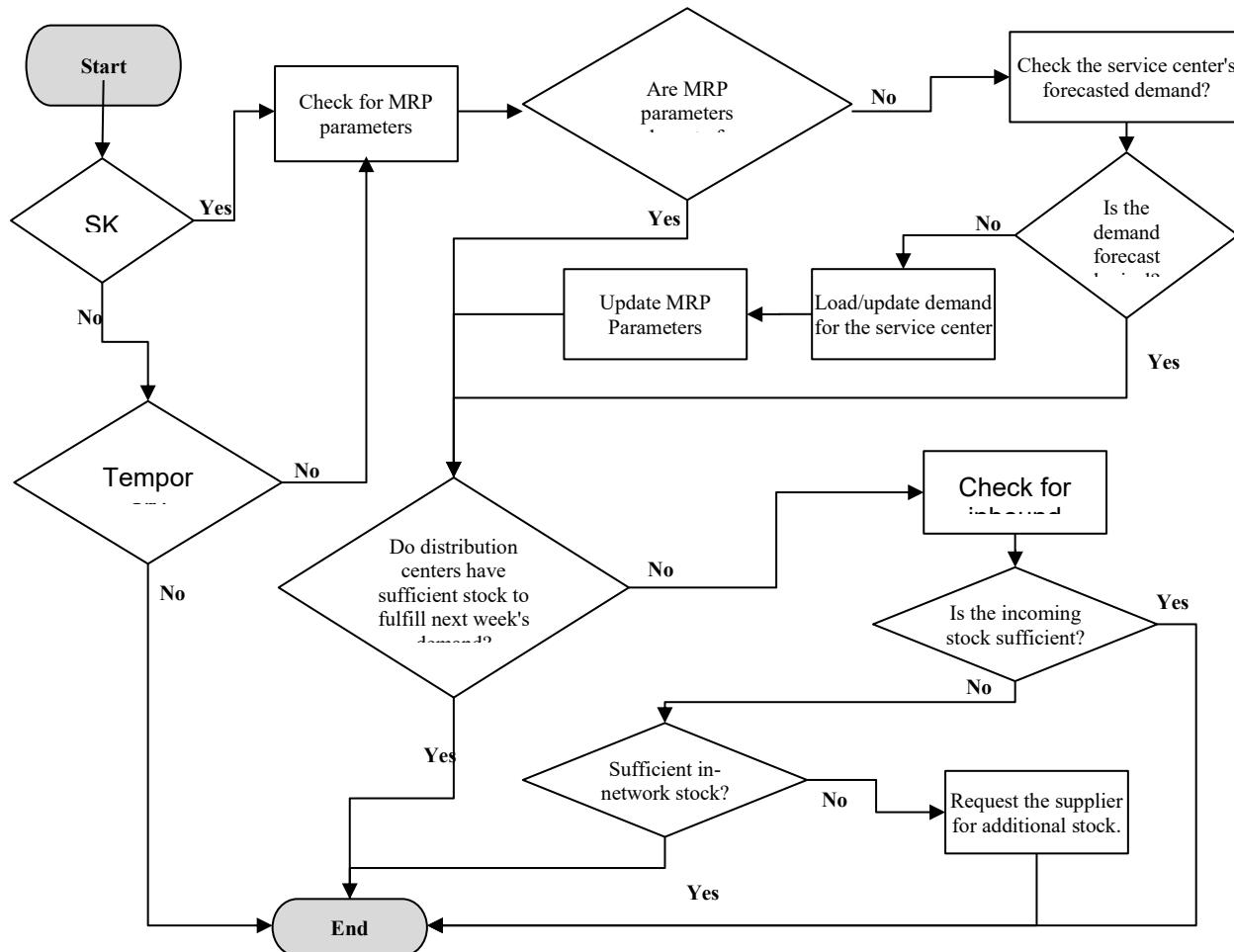


Figure 6: Service Center Fill Rate Review Process Flow.

Source: Author

5.0 Challenges

Despite systematic reviews and automated replenishment processes, several practical challenges can affect consistent fill rate performance across service centers. Some of the challenges are listed below.

5.1 VIN-Specific Parts

Certain parts are vehicle identification number (VIN)-specific and must be ordered only after diagnostic confirmation. These components are inherently reactive in nature and tend to record lower fill rates. Since their demand cannot be accurately forecasted or pre-stocked, opportunities for improvement in this category are limited.

5.2 Storage Constraints for Large Components

Bulky parts such as fascias, axles, and chassis components occupy significant storage space and are typically replenished only upon work order (WO) creation or with reduced stocking parameters. This practice ensures efficient utilization of limited storage capacity but can temporarily impact the overall fill rate.

5.3 Inventory Data Discrepancies

Discrepancies in inventory records often prevent the Material Requirements Planning (MRP) system from operating effectively. When stock quantities are inaccurately recorded—commonly due to delayed or incorrect consumption postings at service centers—MRP may fail to trigger replenishments upon reaching the reorder point (ROP), or conversely, may lead to overstocking. Such data integrity issues undermine the reliability of automated planning and require regular reconciliation.

5.4 Delayed Binning of Delivered Materials

Instances where delivered materials are not promptly binned or recorded into the system are frequently observed. These operational lapses can result in artificial stockouts and preventable fill rate hits, even when physical inventory is available on-site. Addressing process adherence and warehouse discipline is essential to mitigate this issue.

5.5 Field Service Action (FSA) Campaigns

Field service action (FSA) (Abdullah, 2025) campaigns or other large-scale service drives are often initiated with limited prior coordination between service and supply planning teams. Such unplanned campaigns can lead to a sudden influx of vehicles before the necessary parts are replenished at service centers, causing temporary fill rate drops. These instances should be clearly flagged during fill rate reviews, and preventive actions such as proactive restocking before campaign launches should be incorporated into future planning cycles.

6.0 CONCLUSION

A structured and data-driven approach to fill rate review enables organizations to proactively identify operational inefficiencies, supply chain gaps, and forecasting inaccuracies. Integrating MRP data with real-time dashboards and cross-functional feedback loops between service centers, supply chain teams, and suppliers ensures a holistic understanding of fill rate performance. Continuous monitoring, combined with dynamic parameter adjustments and enhanced visibility into part movements, helps sustain high service levels while minimizing excess inventory. Ultimately, consistent root-cause analysis and system-driven replenishment processes build resilience and scalability across the service network, key factors for long-term operational excellence and superior customer satisfaction.

Future work can focus on integrating AI-based forecasting and predictive modeling techniques to enhance fill rate accuracy and responsiveness. Leveraging machine learning and real-time data can enable proactive decision-making and dynamic inventory control (Liu et al., 2025). Ultimately, these advancements can elevate fill rate analysis from a diagnostic tool to a predictive and prescriptive system, offering actionable intelligence for continuous supply chain optimization.

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