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Standardizing the Forecasting Process to Improve On-Time Delivery Performance

A Case Study in a Finnish Engineering and Manufacturing Company

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ABSTRACT:

This study investigates current forecasting practices and their impact on on-time delivery (OTD) performance across different manufacturing units of the case company in Europe. In addition, It considers whether a consistent forecasting process could improve supplier OTD performance at a Finnish engineering and manufacturing company with different sites in Finland, Italy, and the Czech Republic. The research indicates different forecasting approaches across these sites, leading mixed demand signals, planning challenges, and issues on the suppliers shop floor.

This research aims to improve supplier on-time delivery performance by enhancing the current forecasting process. It assesses current forecasting practices across selected manufacturing units, identifies misalignments among them, and investigates the relationship between forecasting accuracy and supplier on-time delivery performance. Furthermore, it offers improvement recommendations for a more standardized forecasting process and proposes a swimlane process flowchart. A mixed-method case study approach is used, combining semi-structured interviews with internal and external stakeholders, with quantitative data analysis of forecasted demand, actual orders, delivered quantity, and OTD performance.

The case companies forecast accuracy is evaluated using MAPE, RMSE, forecast Bias, and forecast Consumption, and then compared with suppliers on-time delivery performance. The research findings show visual differences between selected factories and suppliers in both forecasting accuracy and delivery performance respectively. In most cases, poor forecasting, either under-forecasting or over-forecasting has an impact on low OTD, planning instability, material shortage, and raised operational challenges. Whereas it also indicates that accurate forecasting is not guaranteed good delivery performance, as on-time delivery is also influenced by other factors, such as geopolitical issues, cultural issues, supplier location, transportation, and sub-tier supplier materials issues, which are selected by the case company.

The study concludes that acquiring a standard common forecasting process can support consistent planning, cross-functional alignment across the selected factories, and supplier reliability. Based on these key findings, the study recommends clear roles and responsibilities for the different stakeholders in the case company, including global supply planning, material management, purchasing, and engineering. In addition, it suggests developing a common forecasting process, review routines, and supplier communication to enhance forecasting accuracy and supplier OTD performance.

KEYWORDS: Forecasting, Forecast Accuracy, On-Time Delivery, Lead Time, Standardization

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Abbreviations

BOM- Bill of Materials

CAPA-Corrective and Preventive Action

CIT – Continuous Improvement Team

CR- Change Request

EOL- End of Life

ESU- European Supply Unit

KPI-Key Performance Indicator

LT- Lead Time

MTO- Make-to-Order

MAPE – Mean Absolute Percentage Error

MOQ- Minimum Order Quantity

OTD – On-time delivery

PCBA – Printed Circuit Board Assembly

PO- Purchase Order

PSW- Product Submission Warrant

RC- Root Cause

RCA- Root Cause Analysis

RMSE – Root Mean Square Error

RQ – Research Question

SAP- System Applications and Products in Data Processing

SCM - Supply chain management

SQM – Supplier Quality Management

S&OP- Sales and Operations Planning

1 Introduction

On-time delivery (OTD) performance is very crucial to ensure production continuity and customer satisfaction in the competitive modern manufacturing market. Companies are expected to ship the right products just-in-time as per purchase order confirmation, even if it involves long lead time materials, critical product structures, and fluctuating product demand. As a result, OTD is one of the important key performance indicators (KPIs) to ensure supplier operations reliability. (Chopra, 2019; Syntetos et al., 2016). Whereas supplier On-time delivery (OTD) performance depends not only on their production planning, efficient production lines, capabilities, capacities, and logistics, but also on the visible customer demand forecast to inform planning decisions and on effective communication across the supply chain. As a result, on-time demand forecasts, including forecast time horizon and frozen period, play a crucial role in purchasing, production scheduling, inventory management, and communication with sub-tier material suppliers (Gilliland et al., 2015; Vandepu, 2023).

This study is conducted at a Finnish engineering and manufacturing company with several manufacturing units across Europe, including Finland, Italy, and the Czech Republic, where forecasting demand is vital to ensuring on-time production and material availability. However, this thesis shows that current forecasting practices are neither standardized nor consistent across all selected manufacturing sites. The clear differences in forecast ownership, cross-functional misalignment, forecast breakdown logic, review routines, time horizon, forecast frozen period, and, most importantly, supplier-communicated leads result in inconsistent forecast demand and a lack of transparency across the selected sites. For this reason, suppliers are unable to develop clear production and supply chain plans, leading to poor delivery performance and increased operational inefficiency (Gilliland et al., 2015; Oliva & Watson, 2011; Syntetos et al., 2016). These issues indicate the need for standardizing the forecasting process as a crucial managerial and operational issue within the company.

The main purpose of this thesis is to investigate and analyse the current forecasting process across selected manufacturing sites, demonstrate how forecast accuracy impacts suppliers on-time delivery performance, and finally propose a more standardized forecasting process with a swimlane process flowchart. To achieve these objectives, this case study uses a mixed-method approach, which includes interviews with internal and external stakeholders for qualitative data, as well as a quantitative analysis from forecasted demand, actual orders, delivered quantity, and on-time delivery (OTD) performance (Creswell & Clark, 2017; Yin, 2017). By connecting these research findings with current literature on demand forecasting, forecast accuracy, supply chain management, lead time variability, and cross-functional alignment, this thesis aims to provide both academic insights and practical recommendations, along with a swimlane for improving forecasting consistency and supplier on-time delivery performance. (Chopra, 2019; Gilliland et al., 2015; Oliva & Watson, 2011).

1.1 Research Background and Problem Statement

1.1.1 Research Background

Forecasting demand plays a vital role in manufacturing and operational supply chains, enabling the visualization of the company future material and resource needs in advance and supporting purchasing, supply chain planning, production planning, inventory management, and supplier coordination. Suppliers will face challenges in capacity planning, securing raw materials, and ensuring on-time deliveries if customer demand forecasts are inconsistent, inaccurate, or delayed. For this reason, a good forecast or an accurate forecast can significantly affect component availability, production scheduling, capacity allocation, and on-time delivery performance. (Chopra, 2019; Gilliland et al., 2015; Vandepu, 2023).

In case company, demand forecasting is used for the selected manufacturing units located in Finland, Italy, and the Czech Republic to support supplier production planning and capacity allocation, and to ensure material availability. However, the current fore-

casting process is not fully consistent and aligned among these selected units. In addition, demand forecasts are communicated and shared only with selected suppliers, based on the business case, such as strategic suppliers, high-volume suppliers, and safety-critical component suppliers, rather than with all suppliers. According to the Supplier Quality Management (SQM) monthly rush report, only 70-80% of suppliers receive forecast demand from the selected case company factories. The rest of the suppliers develop their own forecasts based on historical order consumption patterns, which obviously lead to planning instability, expediting costs, inventory risk, and urgent replenishment. Moreover, the lack of clear ownership for demand forecasting, forecast breakdown logic, unstable supply planning, review routines, time horizon, and a forecast frozen period contributes to inconsistent forecasting processes. Therefore, the lack of a standard forecasting process has become a critical issue for the case company, as reliable on-time delivery (OTD) performance depends on stable supply chain planning, transparent coordination, and effective cross-functional alignment.

1.1.2 Problem Statement

The key problem identified in this study is the lack of standardized forecasting practices across the selected case company's manufacturing units in Europe. Furthermore, this thesis identifies discrepancies in the current forecast preparation process, the review routine, stakeholder involvement, and supplier communication. For this reason, every factory follows its own forecasting practices, processes, supply planning methods, forecast review patterns, forecast horizons, frozen periods, and supplier communication for its order confirmation strategies. The study reveals that each unit shares a forecast with selected suppliers at around 70%-80% based on their business case, and the remaining suppliers develop their own forecasts using historical order volume for the time period, including peak seasons. This lack of a standard forecasting process leads to unstable planning, inconsistent demand signals, and greater uncertainty for suppliers. For this reason, suppliers face many issues, including material shortages, inventory management, unstable planning, and poor on-time delivery performance. Therefore, this study

investigates the current forecasting process across different manufacturing sites to assess how forecasting accuracy impacts supplier on-time delivery (OTD) performance, and proposes a suitable forecasting process, with a Swimlane flowchart, to increase supply chain consistency, cross-functional alignment, and improve supplier OTD performance.

1.2 Research Questions

This thesis is guided by three research questions that related to analysing current forecasting practices, forecast accuracy connecting with supplier on-time delivery performance, and the potential standard forecasting process among the selected manufacturing locations in the case company.

1. Research Question 1 (RQ1): What forecasting practices are currently used in the selected manufacturing units of the case company, and how are these forecasting approaches misaligned across units?
2. Research Question 2 (RQ2): How does forecasting performance relate to supplier On-Time Delivery (OTD) performance in the selected manufacturing units?
3. Research Question 3 (RQ3): How can a standardized forecasting process improve cross-functional alignment and supplier On-Time Delivery performance?

1.3 Research Objectives

The main objective of this study is to analyse current forecasting practice and propose a standard forecasting process with a swimlane flowchart to improve supplier on-time delivery performance. The specific objectives are to:

1. Analyze the current forecasting practices used across the selected manufacturing units and identify areas of misalignment.
2. Evaluate how forecasting accuracy relates to supplier on-time delivery performance among the selected manufacturing units.

3. Recommend a standard forecasting process with a swimlane flowchart to enhance cross-functional alignment, stable planning, and ensure supplier On-time delivery performance.

1.4 Research Keywords, Scope, and Limitations

The study indicates the most relevant keywords, scope, and limitations to set the boundaries of this thesis, which are described in below:

1.4.1 Keywords

1. Forecasting: Forecasting is the estimation of future demand based on historical order consumption, customer orders, and market analysis.
2. Forecast Accuracy: Forecast accuracy measures forecasted demand compared with the actual order quantity.
3. Lead Time: Lead time is the time between order placement and product delivery.
4. On-Time Delivery (OTD): On-time delivery is the percentage of orders delivered within the requested and agreed timeline.

1.4.2 Scope

1. The research focuses on the selected European manufacturing units in Finland, Italy, and the Czech Republic.
2. The quantitative analysis is limited to selected external direct material suppliers and is relevant to supplier OTD performance under SQM monthly rush reports.
3. A mixed-method study combining quantitative forecast demand, actual orders, delivered quantity, and supplier OTD data analysis with qualitative interviews involving internal stakeholders and selected suppliers.

1.4.3 Limitations

1. The study does not include manufacturing units located outside Europe.

2. The research does not consider benchmarking comparison with other Finnish companies.

1.5 Expected Research Outcomes and Deliverables

This research is expected to deliver three main study outcomes.

1. Provide a clear and transparent overview of the current forecasting process used across the selected manufacturing units, indicating key forecasting process differences and areas of misalignment.
2. Visualize the impact of forecast accuracy on on-time delivery by analysing different Key performance indicator (KPI) metrics.
3. Propose a set of recommendations for a standard forecasting process with a swimlane flowchart to enhance stable planning, cross-functional alignment, supplier communication, and supplier on-time delivery performance.

2 Literature Review

This literature review covers the key concepts related to forecasting process standardisation and the performance of the suppliers in terms of On-Time Delivery, including supply chain management, demand forecasting, forecasting accuracy, lead time, demand variability, lead time variability, cross-functional alignment, and process standardisation. Additionally, the literature review aligns with the research questions of this thesis. These concepts are essential for identifying current forecasting practices, understanding their impact on supplier delivery performance, and identifying how a standardised process can improve supply chain planning consistency across sites.

2.1 Supply Chain Management and On-Time Delivery

Supply chain management (SCM) provides the theoretical basis for this research, as it explains that materials and information flow are connected among suppliers, factories, and internal stakeholders. In the case company, supplier delivery performance relies not only on supplier capability but also on an accurate demand forecast that is developed, aligned with relevant stakeholders, and communicated with suppliers for review and confirmation. Therefore, Supply Chain Management is directly related to the thesis and shows the direction of the standard supply chain for an accurate forecasting process to improve supplier on-time delivery performance (Chopra, 2019; Christopher, 2016; Swink et al., 2023).

Comparing this research with the literature review shows that forecasting practices in the case company vary across factories in Finland, Italy, and the Czech Republic. Suppliers receive inconsistent demand forecasts and have lower planning visibility. This inconsistency causes material shortages, production schedule updates, higher expediting costs, air shipments, challenges in inventory management, and delivery performance risks. Figure 1 compares good and poor forecasting performance and its impact on supplier on-time delivery. It also highlights the importance of consistent planning, clear communication with suppliers, and strong teamwork across locations. Therefore, the

standard forecasting process is a vital topic in this thesis as it supports better coordination, supplier production preparation, and delivery performance (Christopher, 2016; Oliva & Watson, 2011; Syntetos et al., 2016).

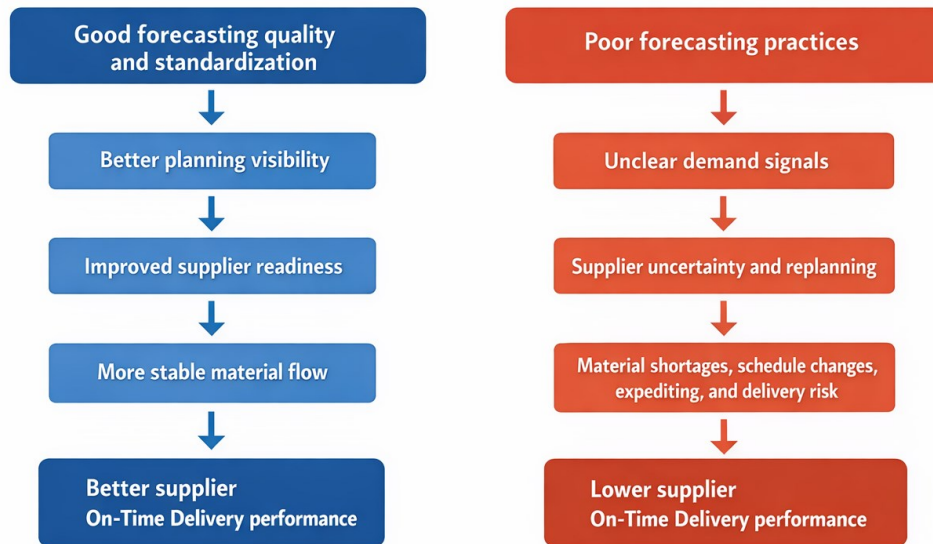


Figure 1: Conceptual relationship between forecasting process and delivery performance (Christopher, 2016).

Overall, this section supports RQ2 and RQ3 by showing that supplier on-time delivery performance depends on reliable supply chain coordination and consistent forecast-based planning across manufacturing sites.

2.2 Demand Forecasting

2.2.1 Demand Forecasting in Supply Chain Management

Demand forecasting plays an important role in supply chain management by estimating future demand from historical consumption data, market analysis, and customer order confirmations (Chopra, 2019; Gilliland et al., 2015). In modern manufacturing, forecast accuracy supports functions such as purchasing, supply chain, production planning, lo-

gistics, inventory management, and supplier communication for demand and order confirmation (Chopra, 2019; Godahewa et al., 2025). Furthermore, Accurate forecasting is important for long-lead-time materials, where suppliers need advanced demand forecasts to plan material availability, ensure capacity, allocate resources, manage inventory, and achieve on-time deliveries (Chopra, 2019; Syntetos et al., 2016).

In this study, forecast accuracy is evaluated by comparing forecasted demand with actual order quantity over the time period. The research considered four KPI metrics, which are MAPE, RMSE, Forecast Bias, and Forecast Consumption. Forecast errors cause significant planning challenges for suppliers. Under-forecasting leads to material shortages, supplier capacity issues, urgent replenishment, resource allocation problems, costly air shipments, and late delivery. Over-forecasting leads to excess inventory, unstable planning, and inefficient use of capacity (González et al., 2025; Hyndman & Koehler, 2006; Jain, 2021).

The literature shows that forecasting accuracy depends not only on the forecasting process but also on other factors like process design, data quality from internal and market analysis, review routines, customer order confirmation, and cross-functional alignment (Gilliland et al., 2015; Oliva & Watson, 2011; Syntetos et al., 2016). Misalignment in forecasting practices across manufacturing sites within the same company results in inconsistent demand signals and inefficient supplier planning. As a result, suppliers cannot deliver the product on time (Oliva & Watson, 2011; Syntetos et al., 2016).

The issue above is relevant to this study because the case company faces challenges not only with forecast errors but also with differences in forecasting practices among European factories, review routines, supplier communication, and local planning logic. This subsection supports RQ1, RQ2, and RQ3 by explaining the importance of forecast accuracy, quality, and standardised forecasting processes to improve supplier delivery performance.

2.2.2 Demand Forecasting in Manufacturing Industry

In the modern manufacturing industry, demand forecasting plays a critical role in supporting purchasing, production scheduling, inventory management, logistics, and supplier coordination. Reliable demand forecasts are particularly essential for components with long lead times, as inaccurate predictions can result in material shortages, excess inventory, urgent restocking, and ineffective delivery execution (Chopra, 2019; Christopher, 2016; Syntetos et al., 2016).

The literature shows that effective forecasting depends on a standard process with clear forecast ownership, consistent demand definitions, a regular review process, and alignment among internal stakeholders. If these factors are weak, forecast information becomes inconsistent and less reliable. This directly relates to the case study company (Gilliland et al., 2015; González et al., 2025; Oliva & Watson, 2011; Syntetos et al., 2016).

Literature shows that many manufacturing companies use separate forecasting practices, but these approach variations add value if this is supported by reliable data, clear standards, and stable planning routines that convert forecasts into stable supplier signals and realistic supplier shop-floor production plans (Gilliland et al., 2015; Hyndman & Athanassopoulos, 2021; Vandepu, 2021).

In summary, this section supports RQ1 by identifying current forecasting practices across all sites that should be common and standardised across manufacturing sites. It also supports RQ3 by demonstrating the importance of consistent processes and alignment in improving forecasting accuracy, reliability, and supplier delivery performance (Oliva & Watson, 2011; Gilliland et al., 2015; Syntetos et al., 2016).

2.3 Forecasting Beyond Historical Demand

Forecasting demand starts with analysing historical demand data to develop a useful baseline. However, for make-to-order and long-lead-time materials, historical demand alone is insufficient. Customer orders can arrive late, project schedules can change, and suppliers require early visibility to plan for materials, capability, and capacity. Therefore,

forecasts should also incorporate forward-looking information, including sales opportunities, quotations, customer commitments, project milestones, and engineering updates, as shown in Figure 2. These inputs can significantly improve visibility, enabling the development of standard demand forecasts and the release of purchase orders or actual orders. However, this input is not effective if there are clear guidelines for reviewing the input and integrated to the demand forecast (Chopra, 2019; Gilliland et al., 2015; Vandeput, 2023).

The literature indicates that judgmental adjustments and causal information are needed when forecasting future demand, especially if factors are missing from historical consumption data. These factors include promotions, price changes, major customer projects, product specification changes, and product phase-in and phase-out. Incorporating this information can enhance forecast relevance. However, manual adjustments can increase bias and affect quality. Additionally, forecasting supports stable planning because frequent updates impact on suppliers delivery execution and manufacturers to revise their plans. This causes capacity issues and reduces delivery performance. To mitigate this risk, a standard forecast-freeze period should be aligned between the customer and the supplier. (Gilliland et al., 2015; Hyndman & Athanasopoulos, 2021; Oliva & Watson, 2011; Syntetos et al., 2016).

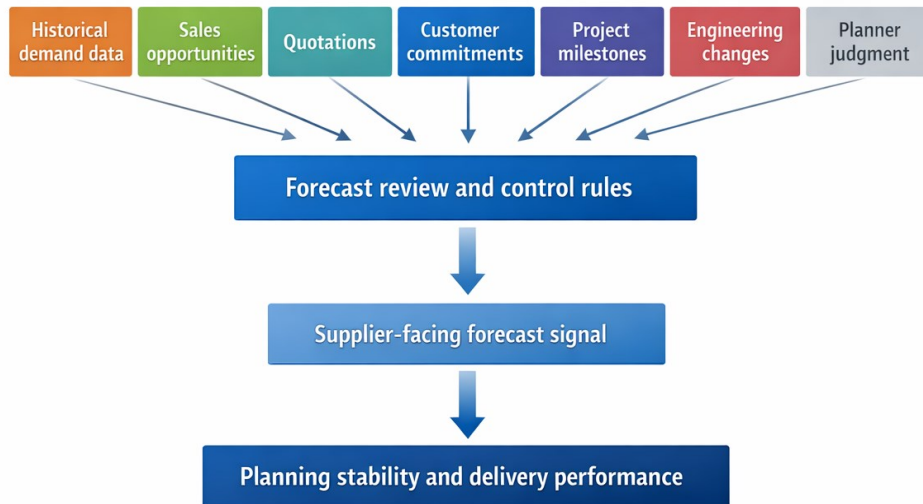


Figure 2: Inputs to Forecasting Beyond Historical Demand (Gilliland et al., 2015; Hyndman & Athanasopoulos, 2021; Oliva & Watson, 2011; Syntetos et al., 2016)

In summary, this subsection addresses RQ1 by showing that robust forecasting requires more than analysing historical demand. Figure 2 shows that historical demand must be combined with prospective information, validated through review and control rules, and then converted into a demand forecast. This improves planning stability and delivery performance.

2.4 Lead Time and Lead Time Variability in Supply Chain

Lead time is an important factor in this study because it affects when a company must plan materials and share forecast information with suppliers. During the forecast development, supply planner should be consider each material lead time, specifically long lead time materials, including safety components. In simple terms, lead time is the time between placing an order and receiving the product and material. In manufacturing, lead time can include production, internal processing, transportation, and receiving the materials from a sub-tier supplier. When lead times are long, supply planners must plan earlier, often before actual customer demand is fully visible, to avoid the business risk. If forecast information is poor in a long-lead-time environment, the risk of material

shortages, inventory issues, urgent restocking, air shipments, and late deliveries increases. Lead time variability makes these challenges more serious, and supply planners need to consider these aspects. This means that lead time is not consistent and may change from one order to another due to issues such as production delays, transportation uncertainties, supplier capacity problems, and unstable supply chain planning, as mentioned as shown in Figure 3. Therefore, delivery performance depends not only on average lead time but also on the stability and predictability of lead time. This is closely relevant for the case study company, where supplier responsiveness and forecast visibility are essential for ensuring OTD performance (Ben-Ammar et al., 2022; De Simone et al., 2023; Mohammed & Mandal, 2023).

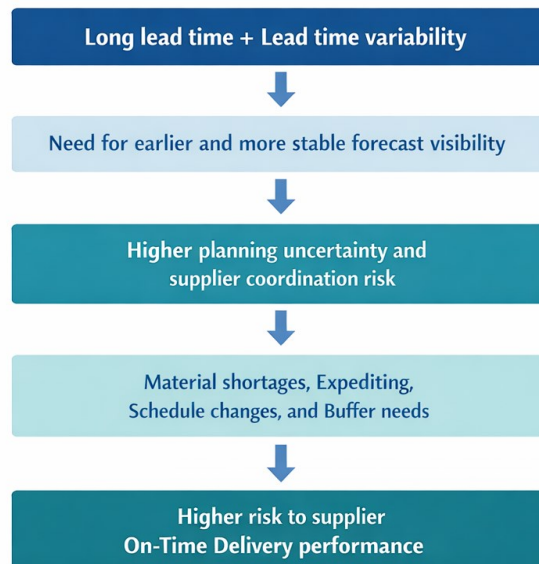


Figure 3: Lead time and Variability effects on supplier delivery performance (Ben-Ammar et al., 2022; De Simone et al., 2023; Mohammed & Mandal, 2024)

In summary, this subsection addresses RQ2 by showing that long lead times must be considered earlier to develop more accurate and consistent forecast information in supplier planning and improve delivery performance. Figure 3 details the process. When lead times are long, early and reliable forecasts become more important. However, forecasting tools sometimes struggle to handle such variability, which complicates planning and increases uncertainty. This uncertainty makes supplier coordination harder, leading to material shortages, urgent shipments, restocking, schedule changes, and buffer stocks.

If these issues grow, suppliers will miss on-time delivery targets (Ben-Ammar et al., 2022; De Simone et al., 2023; Mohammed & Mandal, 2023).

2.5 Demand and Supply Variability in Supply Chain Process

Variability is an important concept in this study because both forecasting and supplier delivery performance are affected by changes in demand and supply over time. Variability refers to the fluctuation between actual and expected orders based on forecasted demand and lead time. On the demand side, it appears as changes in order volumes, timing, demand peaks, seasonal patterns, and urgent project-related demand. On the supply side, it shows in variations in lead times, production outcomes, transportation reliability, and material availability. High variability makes planning more challenging because the supply chain must respond to greater uncertainty. Even a forecast that seems acceptable overall can cause operational issues if short-term fluctuations are large and frequent. The literature shows that high variability impacts material planning, leading to more frequent rescheduling and less stable supplier response. This raises the risk of material shortages, urgent restocking, resource allocation problems, late deliveries, and inefficient inventory planning. Therefore, this thesis does not focus solely on forecast accuracy as a number. It also considers whether the planning process produces stable, useful signals for suppliers and factories. This perspective is important for understanding the current challenges in the case company and for recommendations at the end of the study (Ben-Ammar et al., 2022; Mohammed & Mandal, 2023).

Thus, this subsection supports RQ2 by indicating that the analysis considers not only forecast accuracy but also the stability of demand and supply signals, which influence supplier performance and operational risk.

2.6 Forecasting Accuracy, Responsiveness, and the Trade-Off

The literature shows that an accurate forecast supports reliable supply chain performance. When demand forecasts are precise, suppliers can better align purchasing, in-

ventory management, production scheduling, and sub-tier supplier planning with demand. This alignment helps minimise material shortages, transportation issues, excess inventory, and delivery problems. However, the literature also indicates that forecast accuracy alone is not sufficient. A forecast creates value only when the supply chain can respond to it structurally. This creates an important balance for this study. On one hand, companies want flexible and responsive supply chains that quickly react to demand changes. On the other hand, frequent last-minute changes can cause instability for suppliers and factories. Therefore, the objective is not only to improve forecast accuracy but also to develop a forecasting process aligned with the cross-functional team to provide a stable supply chain. This perspective aligns with the recommendations and conclusions of this thesis, which highlight the need for a standardised process, clear guidelines, and improved cross-functional planning (Ben-Ammar et al., 2022; de Arquer et al., 2022; De Simone et al., 2023).

This subsection addresses Research Question 2 (RQ2) by examining the impact of forecasting accuracy, responsiveness, and stability on supplier readiness and delivery reliability.

2.7 Forecast Accuracy Measurement and Key Performances Indicators

Forecast accuracy measurement is an important factor in this study for evaluating the supply chain planner efficiency and comparing forecasted demand with the actual order quantity. Forecast accuracy assessment helps evaluate the reliability of forecast information for effective supply planning and decision-making, ensuring a smooth business. In this study, forecasting accuracy is evaluated using four key performance indicators (KPIs) shown in below figure 4, which are Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Forecast Bias, and Forecast Consumption. These indicators are selected because they capture forecast error size, forecast error direction, and the practical realisation of forecasted demand. This approach ensures a balanced and relevant evaluation of demand forecast quality from a business perspective (Davydenko & Fildes, 2013; Hyndman & Koehler, 2006; Oracle, 2026).

The forecasting literature recommends using multiple KPIs because no single measure fully captures forecast performance. In this study, MAPE measures relative forecast accuracy, RMSE indicates the size of forecast error in actual orders, Forecast Bias identifies patterns of over- or under-forecasting, and Forecast Consumption evaluates the proportion of forecasted demand compared to actual demand. These four KPIs provide a practical and balanced view of forecasting performance in the case company. Figure 4 shows an overview of the KPI framework used in this thesis. It compares forecast demand with actual orders and analyses them using four indicators (Davydenko & Fildes, 2013; Hyndman & Koehler, 2006; Oracle, 2026).

These KPIs are valuable because those KPIs provide both statistical and operational interpretations of forecast accuracy. RMSE shows significant forecast deviations, while Bias indicates whether forecast errors are consistently positive or negative. Additionally, forecast consumption offers a straightforward business view of forecasted demand consume. The literature shows that good forecast accuracy can improve supply chain performance, including lower inventory and overhead costs and better delivery performance. These benefits depend on properly using demand forecast information in supply planning and execution. Therefore, the KPI results in this thesis are compared with the suppliers on-time delivery performance to better understand their operational impact (Davydenko & Fildes, 2013; Hyndman & Koehler, 2006; Oracle, 2026).

This section supports RQ2 by providing the KPI basis to evaluate how forecasting performance relates to supplier On-Time Delivery performance.

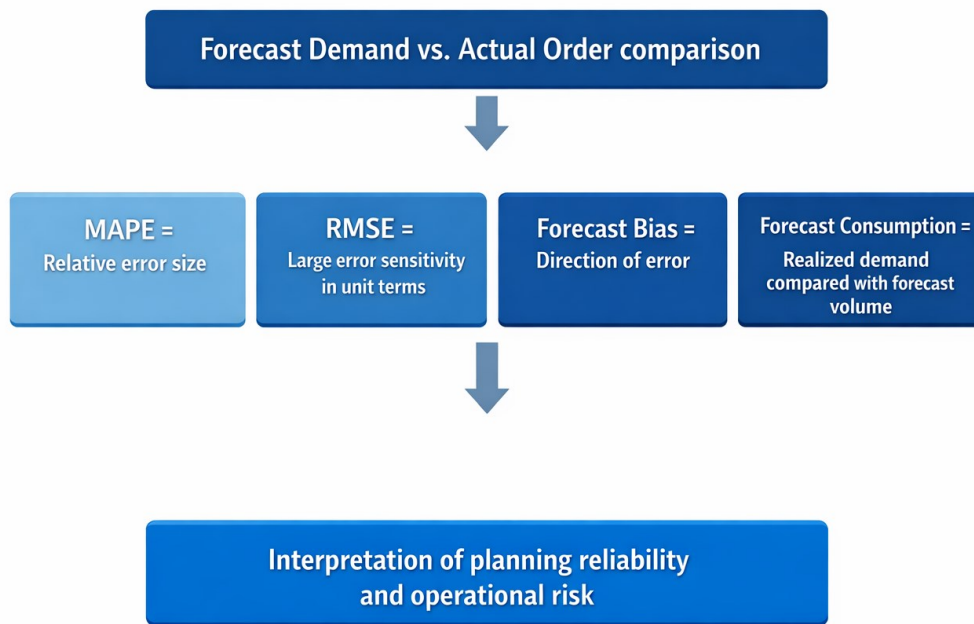


Figure 4: Forecast Performance KPI framework (Davydenko & Fildes, 2013; Hyndman & Koehler, 2006; Oracle, 2026).

2.8 Cross-Functional Alignment in Demand Forecasting

Cross-functional alignment is important for accurate demand forecasting because demand information impacts purchasing, production planning, inventory management, and supplier coordination. When stakeholders use different planning logic, forecasts become inconsistent and implementation unstable. In this study, cross-functional alignment is relevant, as the case company faces variations in forecasting practices across manufacturing units in Europe, which affect supply planning consistency and supplier visibility of upcoming demand (Chopra, 2019; Gilliland et al., 2015; Syntetos et al., 2016).

Sales and Operations Planning (S&OP) is recognised in the literature as a critical factor in enhancing cross-functional alignment within organisations. S&OP facilitates a unified understanding of demand, supply, and capacity. By establishing clear roles, structured review routines, and defined decision-making responsibilities, S&OP enables functions to operate on a shared forecast and reduces conflicting actions. Consequently, improved cross-functional alignment results in a standardised forecasting process and generates

more consistent demand signals for suppliers (Gilliland et al., 2015; Oliva & Watson, 2011).

This section supports RQ3 by showing that a standardised forecasting process requires strong coordination across functions and sites. Better alignment improves planning consistency, supplier visibility, and On-Time Delivery performance.

2.9 Forecasting Process Standardization and Governance

The standard forecasting process uses a consistent approach to prepare, review, and share forecasts throughout the organisation. It should include clear definitions, process flow, stakeholder involvement, forecast horizon, frozen period, clear roles, review routines, and supplier communication for alignment, as shown in Figure 5. In a multi-site manufacturing environment, this standardisation is crucial because inconsistent forecasting practices can cause unstable demand signals for suppliers. When suppliers receive late forecasts or orders and face frequently changing demand, they face challenges in planning capacity, allocating resources, securing materials, managing inventory, managing logistics, and ensuring timely deliveries. Therefore, a harmonised forecasting process is important to improve supplier delivery performance (Gilliland et al., 2015; Syntetos et al., 2016).

In the absence of forecast standardisation, individual units may implement varying definitions of demand forecast, ownership, and the forecast review process. Such inconsistency diminishes transparency and undermines the reliability of supplier demand information. Implementing a standardised forecast process clarifies roles, responsibilities, and ownership of forecast changes, while designating specific stakeholders to review and align forecast deviations. Consequently, suppliers receive more stable and timely demand forecasts, which enhance capacity planning, material preparation, resource allocation, inventory management, and supplier on-time delivery (Davydenko & Fildes, 2013; Syntetos et al., 2016).

Standardisation enhances governance by establishing a foundation for accountability, forecast accuracy evaluation, and ongoing improvement, supported by a dedicated team.

When common process rules are implemented, Key Performance Indicator (KPI) results become more meaningful and comparable across sites. Figure 5 shows that collaboration among teams from different stakeholders makes the forecasting process more consistent. Collaboration also helps coordinate with suppliers and ensures orders are delivered on time.

This section supports RQ 3 by showing that a standardised forecasting process can improve supplier delivery performance through stable demand forecasting communication, better supply chain planning visibility, and avoiding disruptions to supply and delivery performance (Hyndman & Koehler, 2006; Oliva & Watson, 2011)

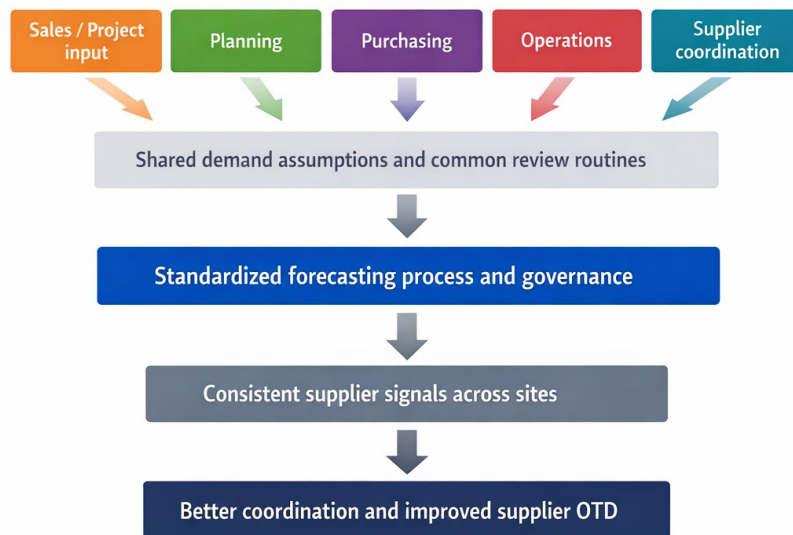


Figure 5: Forecasting Process Standardization and Governance (Hyndman & Koehler, 2006; Oliva & Watson, 2011)

2.10 Literature Synthesis and Research Gap

The reviewed studies show that forecasting accuracy in industry depends on more than the forecasting process. Statistical frameworks and data quality are also important. Forecast quality depends on standard processes and review routines with relevant stakeholders. Cross-functional collaboration and integrating forecast demand information into supply chain planning are also key. Demand Forecasting should be seen as

a core part of the overall supply chain planning system, not a separate technical function. This study highlights the need for cross-functional alignment and robust standard forecasting processes to improve forecast accuracy (Chopra, 2019; Gilliland et al., 2015; Oliva & Watson, 2011; Watson & Kraiselburd, 2007)

The literature reviewed is divided into three main categories. The first focuses on the forecasting process, data, and accuracy. The second covers supply chain and operational factors such as lead time, variability, planning stability, and supplier responsiveness. The third examines process design, governance, clear ownership, and cross-functional alignment. These findings indicate that forecast accuracy alone does not improve supplier delivery performance. Forecast information should be stable and consistently managed to enable suppliers and internal stakeholders to take effective action (Hyndman & Athanopoulos, 2021; Oliva & Watson, 2011; Syntetos et al., 2016; Yani & Aamer, 2023).

Furthermore, the literature review reveals a research gap relevant to this study. Several studies address improvements in forecast accuracy and the impact of collaborative planning on supply chain performance. However, fewer examine how differences in forecasting practices across manufacturing sites affect supplier-facing outcomes in a multi-site industrial context. Limited research shows process standardisation enhances comparability, transparency, and coordination when demand forecast information is communicated only to selected suppliers. This gap is especially relevant to the case company, where forecast ownership, supplier communication, review routines, and supplier visibility differ among units. The case company also shares forecast information only with selected suppliers based on business and product cases. Therefore, this study contributes by investigating the relationships among forecasting accuracy performance, supplier delivery performance, and process standardisation within selected factories and suppliers (Gilliland et al., 2015; Oliva & Watson, 2011; Syntetos et al., 2016; Yani & Aamer, 2023).

Overall, the literature review provides the analytical basis for the study. Regarding RQ1, it indicates that the current forecasting process can be investigated through tools and inputs, clear forecast ownership, forecast review routines, supplier communication, and

cross-functional consistency across sites. For RQ2, it shows that the relationship between forecasting accuracy and supplier delivery can be assessed using factory-level forecast accuracy, bias, consumption, actual orders, and supplier capability. For RQ3, it supports the view that a standard forecasting process should include governance, cross-functional alignment, and supplier-oriented planning rules.

3 Methodology

3.1 Research Design

This research uses a mixed-method case study design, which is convenient for investigating both the current forecasting process and supplier delivery performance measurement by using the KPI metric. The qualitative method, using interviews with relevant internal and external stakeholders, shows the preparations for forecasting, review, and communication from the selected manufacturing units. The quantitative method indicates forecast accuracy using forecast demand, actual orders, delivered quantity, and supplier On-time delivery performance data. Using both methods provides a more comprehensive understanding of the research problem and develops recommendations for the future process (Creswell & Clark, 2017). The case study approach is selected because the research focuses on one company across several manufacturing sites that follow different forecasting processes. This research design allows the study to analyze forecasting practices, supply planning activities, supplier communication, and supplier delivery performance measurement. Furthermore, this approach supports the aim of the thesis, which is to gain a clear understanding of the current process and propose recommendations for the continuous improvement (Yin, 2017)

The case company is a Finnish engineering and manufacturing organization with multiple manufacturing units across Europe, including Finland, Italy, and the Czech Republic. These locations were chosen due to their direct involvement in demand forecasting, global supply planning, supplier communication, and delivery execution. This selection facilitates an investigation into variations in current forecasting practices and their potential impact on supplier on-time delivery performance.

The selected research design addresses all three research questions and objectives. Qualitative methods address research question 1 (RQ1) by identifying current forecasting practices and areas of misalignment. Quantitative methods address research question 2 (RQ2) by evaluating forecasting performance (accuracy) in relation to supplier OTD

performance. By integrating both qualitative and quantitative evidence, the research addresses research question 3 (RQ3) by proposing recommendations for a standardized forecasting process, including a swimlane process flowchart.

3.2 Data Collection

The research evaluates the research questions using both primary and secondary data. Primary qualitative data come from semi-structured interviews with relevant internal stakeholders and selected suppliers. Secondary quantitative data is gathered from the case company internal forecast data platforms, including SAP and Qlik, as well as delivery performance-related data from the SQM monthly validation letter. This includes forecast demand, actual order quantities, and supplier delivery performance data. Combining both data types provides numerical supplier delivery performance evidence with practical process insights (Yin, 2017)

The data collection approach is designed to evaluate forecast accuracy and supplier delivery performance, and to identify the reasons for any differences between them. Quantitative data provide evidence of forecast accuracy and supplier OTD performance, while qualitative interview data explain current forecasting practices, manufacturing site-level differences, and areas for improvement.

3.2.1 Quantitative Data Collection

Quantitative data collected from the case company's internal platform, such as SAP and Qlik, which contains historical demand forecasts. In addition, the SQM monthly validation letter records actual orders and supplier delivery performance for the selected factories and selected suppliers under the SQM scope. This quantitative dataset is used to compare demand forecasts with actual orders over the time periods and to analyze their relationship and impact on supplier OTD performance at the factory level.

3.2.2 Qualitative Data Collection

Qualitative data are gathered through semi-structured interviews with both internal stakeholders and selected external suppliers. Internal stakeholders represented the main functions involved in forecasting and supplier coordination, including purchasing, materials management, global supply planning, and supplier quality management. In total, 34 internal stakeholders and 20 external suppliers from five different tribes were interviewed. The selected supplier group included strategic suppliers, safety-component suppliers, global suppliers, and those with poor delivery performance.

Semi-structured interviews are chosen for this thesis because they provide a clear structure while enabling participants to explain their experiences in detail. This method helped identify current forecasting practices, misalignments between manufacturing sites, key challenges, and areas for improvement.

3.3 Data Sources and Case Selection

Quantitative data are collected from the case company internal data platform, such as SAP and Qlik, as well as from the SQM Monthly Validation Letter Excel file for the rush report. In addition, demand forecasts are gathered from material management team forecast files, SAP, Qlik, and supply planning records. Furthermore, actual order and delivery quantities, along with on-time delivery (OTD) performance percentages, are extracted from the SQM Monthly Validation Letter Excel file.

Table 1: Data sources and Case factory selection

Data Types	Data Source	Selection Criteria
Forecast Demand	SAP, Qlik, and Excel forecast files from MM	Comparable forecast data available (2025-2026)
Actual Order and delivered quantity	SAP, Qlik, and SQM monthly Validation letter excel	Comparing historical data (2025-2026)
OTD Performance	SQM monthly validation letter excel files	OTD data available for the selected supplier case
Factory Selection	European Manufacturing Network	Data availability, Visible comparison, and same time zone
Interview Data	Interview notes and team records	Key functions, and relevant supplier categories

The data covers from 2025 to 2026 for the quantitative analysis and evaluation. For each month, forecast demand, actual order quantities, delivered quantities, and OTD data are compared. Selected supplier and unit factory pair analyzed as a distinct unit. Factories located in Finland, Italy, and the Czech Republic were purposively chosen as part of the same European manufacturing network, operate within the same time zone for cross-functional team communication, use forecasting in supplier planning, and offer comparable data. Supplier cases were selected based on business relevance and data availability, including strategic, high-volume, and safety-component delivery suppliers. The KPI metric analysis considered only those cases with comparable forecast, actual order quantity, delivered quantity, and on-time delivery (OTD) data available. Furthermore, Interview participants were selected from key internal stakeholders teams and selected suppliers who receive forecasts from materials management (MM) and supplier planning, as well as regular performance follow-up by supplier quality management (SQM).

Table 2 and Figure 6 illustrates the primary data types, data sources, and case selection criteria used in this study.



Figure 6: Data Types and Sources

3.4 Sampling

This study uses purposive sampling, meaning samples are selected based on their relevance to the research and data availability. Specifically, factories, suppliers, and interview participants are chosen for their direct involvement in the forecasting process, material planning, and ensuring material availability in factories. These participants also contribute to production continuity, supplier communication, and on-time delivery performance. In total, 15 suppliers have been selected for their direct deliveries to the chosen factories within the case company. Additionally, feedback on the current forecasting process is provided by 24 internal and external stakeholder participants across the manufacturing sites. The study focuses on five factories located in Finland, Italy, and the Czech Republic. By concentrating on individual case, this approach aligns well with the case study methodology (Palinkas et al., 2013; Yin, 2017).

Five manufacturing units in Finland, Italy, and the Czech Republic are selected because they are part of the forecasting process and demonstrate notable differences in local practices and supplier-delivery performance. To capture relevant perspectives, internal interview participants selected from key functions influencing demand forecasts, including purchasing, material management, global supply planning, and Supplier Quality Management (SQM). Additionally, 15 selected suppliers included to provide insights into forecast visibility, alignment, communication, planning stability, and delivery issues. For the quantitative analysis, supplier cases chosen based on both data availability and business relevance, ensuring comprehensive coverage of the topics under study.

3.5 Data Analysis

3.5.1 Quantitative Data Analysis

The quantitative data analysis evaluates forecast accuracy by comparing the demand forecast with actual order volumes for the same time frame. Four key performance indicator (KPI) metrics have been used for calculation: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Forecast Bias, and Forecast Consumption. Each of these indicators evaluates a different aspect of forecasting accuracy. After analysing these KPIs for the selected supplier delivery cases, the results are compared with supplier OTD performance to identify possible patterns between forecasting accuracy and on-time delivery performance (Davydenko & Fildes, 2013; Jain, 2021). In the quantitative analysis, the forecasted demand and the actual order quantity are compared for each period. If the actual order quantity in period t is denoted as A_t and the forecasted demand in the same period is denoted as F_t , the forecast error is the difference between these two values. The forecast error is defined as $e_t = A_t - F_t$. This comparison provides a full review period, allowing both monthly deviations and overall forecasting patterns to be examined for the selected supplier or the unit factory case (Vandeput, 2021).

Mean Absolute Percentage Error (MAPE) measures the average absolute forecast error as a percentage of the actual order quantity. A lower MAPE value indicates good forecast

accuracy. This KPI metric is useful because it allows comparison across cases with different demand forecast volumes. However, MAPE should be interpreted carefully when the actual order quantity is very low, as the percentage error may become misleading. Additionally, MAPE does not indicate whether the forecast is consistently too high or too low, so it can be analyzed alongside forecast bias and forecast consumption (Bobbitt, 2021a; Davydenko & Fildes, 2013; Hyndman & Koehler, 2006).

Equation 1: Mean Absolute Percentage Error (MAPE)

$$\text{MAPE (\%)} = \frac{1}{n} \sum_{t=1}^n \left(\frac{|A_t - F_t|}{|A_t|} \right) \times 100 \quad (\text{Bobbitt, 2021a}) \quad (1)$$

Table 2 indicates that an MAPE below 10% indicates excellent accuracy. A value between 10% and 20% shows good accuracy. A value between 20% and 30% might be considered acceptable, but the case company sets a high standard, so this range is not acceptable. This range suggests a need for further review and refinement of forecasting accuracy. Values between 30% and 50% indicate poor forecasting, while values above 50% represent very poor performance (Moselle, 2026).

Table 2: MAPE Severity Scale (Moselle, 2026)

MAPE % Scale	Severity
< 10%	Excellent forecasting accuracy
10–20%	Good forecasting accuracy. In this study, Case company take 20% is Good and Acceptable level.
20–30%	Acceptable forecasting accuracy. Case company set the bar high, which is why this range is not acceptable.
30–50%	Poor. Significant improvement needed
> 50%	Very poor. Mmajor issues exist in the forecast model

Root Mean Square Error (RMSE) is a metric that compares forecasted demand values with actual observed values (Hyndman & Athanasopoulos, 2021). Basically, RMSE measures the average size of forecast error by giving more weight to large deviations. In this study, it is calculated as the square root of the average squared difference between actual order quantities and forecast demand. A lower RMSE value indicates better forecasting performance. RMSE is useful because significant forecasting errors can lead to

risks of shortages, the need for urgent replanning, pressure on supplier capacity, and excess inventory. Therefore, monitoring RMSE in this study helps identify and mitigate these operational risks (Davydenko & Fildes, 2013; Hyndman & Koehler, 2006)

Equation 2: Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (A_t - F_t)^2}{n}} \quad (\text{Bobbitt, 2021b}) \quad (2)$$

where n is the number of periods

Forecast Bias indicates the direction of forecasting errors, helping determine whether demand forecasts are usually over- or under-actual orders over time. In this study, this concept is measured as the cumulative signed error relative to cumulative actual orders, thus providing insight into systematic forecasting tendencies.

Equation 3: Bias

$$Bias = \frac{1}{n} \sum_{t=1}^n (A_t - F_t) \quad (\text{Davydenko \& Fildes, 2013}) \quad (3)$$

Equation 4: Forecast Bias

$$Forecast\ Bias\ (\%) = \frac{\sum_{t=1}^n (A_t - F_t)}{\sum_{t=1}^n A_t} \times 100 \quad (\text{Davydenko \& Fildes, 2013}) \quad (4)$$

With this sign convention, a positive bias indicates that the forecast demand is higher than the actual order quantity, while a negative bias indicates that the forecast demand is lower than the actual order quantity. Bias is important because it reveals whether forecast errors follow a consistent pattern over time. Therefore, this KPI metric helps differentiate between random forecasting errors and systematic over- or under-forecasting, underscoring the value of monitoring bias to improve forecasting accuracy (Hyndman & Koehler, 2006; Jain, 2021; Vandeput, 2021)

Forecast Consumption measures the amount of forecasted demand consumed during the same period. In this research, it is calculated as Forecast consumption = (Actual Order / Forecast Demand) \times 100. A value below 100% means the forecast demand is higher than the actual order, while a value above 100% means the actual order quantity is

higher than the forecasted demand. This KPI metric provides a simple business view of forecast realization and shows the amount of forecasted demand that has been used (Chopra, 2019; Oracle, 2026; Vandeput, 2021).

Equation 5: Forecast Consumption

$$\text{Forecast Consumption (\%)} = \left(\frac{\sum_{t=1}^n A_t}{\sum_{t=1}^n F_t} \right) \times 100 \quad (5)$$

Once the KPIs are calculated, they are compared to supplier OTD performance to show the link between forecast accuracy and on-time delivery. This analysis clarifies how forecast accuracy affects delivery, such as risks of shortages, excess inventory, planning instability, and urgent replenishments.

3.5.2 Qualitative Data Analysis

The qualitative interview data have been analysed using thematic analysis. First, the interview questionnaire developed and shared with all participants in advance to support both preparation and analysis. The main themes of the questionnaire included correct forecasting practices and stakeholder involvement, the forecast breakdown process, forecast ownership, supplier communication for reviewing forecast demand based on product lead time, the supplier order confirmation process, KPI usage, and the need for process standardization. This thematic analysis helps identify current forecasting practices across factories and shows which stakeholder groups are involved.

Qualitative analysis through interviews with internal and external stakeholders is crucial. Numerical data alone cannot clarify how forecasts are developed or what the preparation process involves. Current practices also vary across units and forecasting challenges have emerged over time. The interview findings have been combined with quantitative KPI results to create a clearer understanding of the existing forecasting process and to identify areas for improvement within the case company.

3.6 Reliability and Validity

The reliability of the case study is supported using identical data sources, KPI definitions, and calculation methods across all cases. Data on forecast demand, actual orders, delivered quantity, and supplier on-time delivery performance were analysed using consistent processes. For the qualitative data, all stakeholders and participants were interviewed using the same themes and patterns. This structured approach improved consistency and comparability across interviews.

Validity is supported by combining both qualitative and quantitative data. Interview findings are compared with the case company internal data on forecasting accuracy and supplier on-time delivery performance. This comparison confirms whether the findings from quantitative and qualitative research are consistent across different data sources. In addition, validity is further strengthened by selecting participants who are directly involved in supplier forecasting development, forecast breakdown, forecast sharing with the supplier, and supplier communication. Therefore, these findings are closely relevant to the research background, problem, and research questions, making the conclusion more reliable.

4 Results and Discussion

4.1 Quantitative Data Calculation Results

Forecasting accuracy, or forecasting performance, is calculated by comparing forecast demand (F_t) and actual order (A_t) in each period. Monthly forecast errors are calculated, and results across periods are summarized using four metrics, which are MAPE, RMSE, Forecast Consumption, and Forecast Bias. These metrics reflect forecast accuracy, error size, forecast realization, and bias in over- or underestimating demand.

4.1.1 Supplier A Forecasting and OTD Performance

This section presents the results and analysis of forecasting performance from Factory 1 and Factory 2, and supplier A OTD performance at Factory 1 in Finland and Factory 2 in Italy. It explores the correlation between forecasting accuracy and delivery performance in factories and supplier A.

1. Supplier A Forecasting and OTD Performance for Factory 1 (Finland)

Table 3: MAPE Calculation for Supplier A (Factory 1, Finland)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $ A_t - F_t / A_t$
May-25	690	560	-130	130	23.21%
Jun-25	690	1213	523	523	43.12%
Jul-25	690	1149	459	459	39.95%
Aug-25	690	656	-34	34	5.18%
Sep-25	690	800	110	110	13.75%
Oct-25	690	713	23	23	3.23%
Nov-25	1202	541	-661	661	122.18%
Dec-25	1102	688	-414	414	60.17%
Jan-26	1006	648	-358	358	55.25%
Feb-26	880	408	-472	472	115.69%
Mar-26	1005	909	-96	96	10.56%
Apr-26	928	842	-86	86	10.21%
Total Average	10263	9127	-1136	3366	MAPE = 41.88%

The forecast accuracy calculations are presented below for Factory 1:

Σ Forecasting Demand = 10263

Σ Actual Order Quantity = 9127

Forecast Bias = $(10263 - 9127) / 9127 \times 100 = +12.45\%$

Forecast Consumption = $9127 / 10263 \times 100 = 88.93\%$.

MAPE is the arithmetic average of the 12 monthly APE% values, MAPE = 41.88%

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(1490772 / 12)} = 352.46$

Table 4: Supplier A OTD Summary (Factory 1 Finland)

Metric	Value
Σ Forecasting Demand	10263
Σ Actual Order Quantity	9127
Σ Delivered Quantity	8366
Overall OTD%	91.66%

As indicated in Tables 3 and 4, Supplier A at Factory 1 in Finland has faced forecasting challenges and missed delivery targets. A forecast bias of +12.45% and a forecast consumption of 88.93% indicate that forecast demand is frequently over-forecast, leading to excessive capacity planning, surplus inventory, and unclear demand signals. The MAPE of 41.88% shows poor forecast accuracy from factory 1, and an RMSE of 352.46 marks significant monthly fluctuations in units. Supplier OTD is 91.66%, which is short of the 2025 target of 98% and the 2026 target of 99%, as shown in Figure 7. Factory 1 should focus on forecast accuracy and stability to improve supply planning and support supplier A delivery performance.

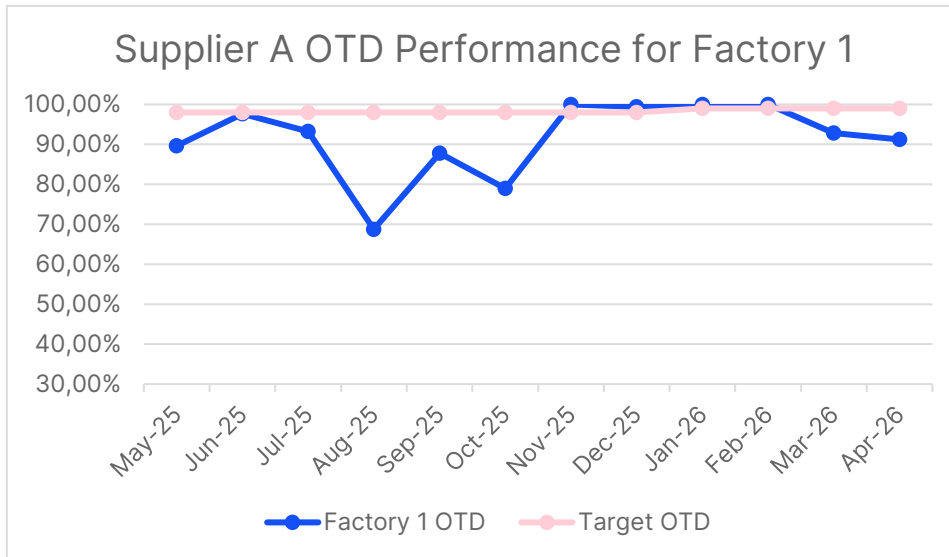


Figure 7: Supplier A OTD Performance for (Factory 1, Finland)

2. Supplier A Forecasting and OTD Performance for Factory 2 (Italy)

Table 5: MAPE Calculation for Supplier A (Factory 2, Italy)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $\frac{ A_t - F_t }{A_t}$
Feb-25	7064	6234	-830	830	13.31%
Mar-25	6872	5895	-977	977	16.57%
Apr-25	6574	5959	-615	615	10.32%
May-25	5992	6018	26	26	0.43%
Jun-25	5772	5271	-501	501	9.50%
Jul-25	7340	6876	-464	464	6.75%
Aug-25	2746	2755	9	9	0.33%
Sep-25	5769	5775	6	6	0.10%
Oct-25	5603	5646	43	43	0.76%
Nov-25	3092	3104	12	12	0.39%
Dec-25	1765	1779	14	14	0.79%
Jan-26	7308	2323	-4985	4985	214.59%
Total / Average	65987	57635	-8262	8482	MAPE = 22.82%

The forecast accuracy calculations are presented below for Factory 2:

Σ Forecasting Demand = 65987

Σ Actual Order Quantity = 57635

Forecast Bias = $(65987 - 57635) / 57635 \times 100 = +14.34\%$

Forecast Consumption = $57635 / 65987 \times 100 = 87.46\%$.

MAPE is the arithmetic average of the 12 monthly APE%, MAPE = 22.82%

$$\text{RMSE} = \sqrt{\frac{\sum(A_t - F_t)^2}{n}} = \sqrt{\frac{27341158}{12}} = 1509.45$$

Table 6: Supplier A OTD Performance (Factory 2 Italy)

Metric	Value
Σ Forecasting Demand	65987
Σ Actual Order Quantity	57635
Σ Delivered Quantity	48640
Overall OTD%	84.39%

Tables 5 and 6 show that Supplier A faces problems with forecasting accuracy from factory 2 in Italy, and Supplier A delivery performance is under the target. A Forecast Bias of +14.34% and Forecast Consumption of 87.46% indicate that forecasted demand is much higher than actual orders. This increased inventory risk, inefficient resource allocation, and planning issues create confusion for the supplier. The MAPE of 22.82% indicates the forecasts are not accurate, while the RMSE of 1509.45 indicates a high error in monthly forecasts. The supplier on-time delivery (OTD) rate is only 84.39%, which does not meet the 2025 target of 98% or the 2026 target of 99%. Figure 8 shows this OTD trend. Overall, the data shows that bad forecasts made planning harder and delivery less reliable. Factory 2 needs more reliable forecasts for Supplier A to ensure on-time delivery.

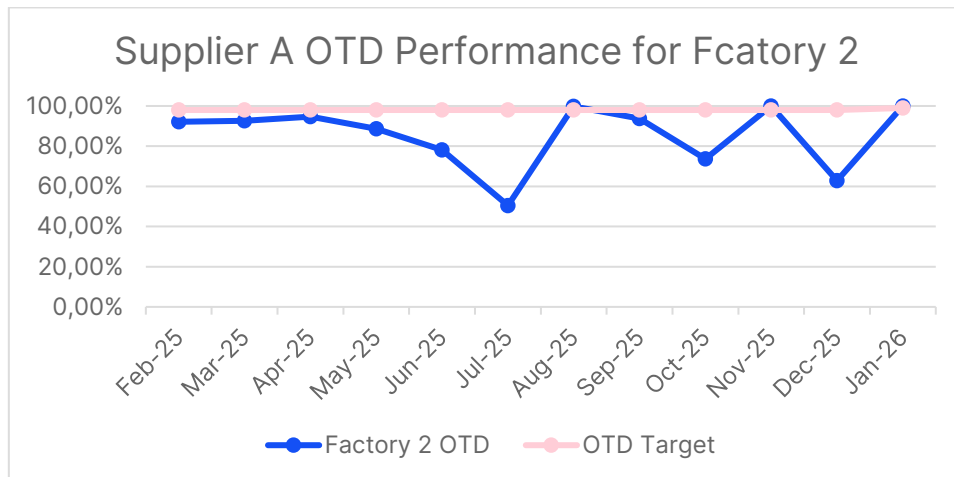


Figure 8: Supplier A OTD Performance for Factory 2, Italy

3. Comparative Analysis of Supplier A for Factory 1 and Factory 2

Table 7: Comparative Analysis of Supplier A Forecasting and OTD Performance

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 1 (Finland)	41.88%	352.46	+12.45%	88.93%	91.66%	Planning and inventory
Factory 2 (Italy)	22.82%	1509.45	+14.34%	87.46%	84.39%	Higher inventory

Table 7 indicates that Supplier A experienced forecasting challenges from both factories, and Supplier A failed to meet OTD targets for both factories. Factory 2 has a lower MAPE of 22.82% compared to Factory 1 41.88%, demonstrating good forecast accuracy by percentage compared to Factory 1. However, factory 2 RMSE is substantially higher at 1509.45, relative to Factory 1 352.46, indicating that factory 2 forecast errors are larger in absolute terms. Both factories show positive forecast bias and forecast consumption below 100%, reflecting a consistent tendency to over-forecast. Factory 1 reported a forecast bias of +12.45% and forecast consumption of 88.93%, while factory 2 reported +14.34% and 87.46%, indicating a slightly higher degree of over-forecasting at factory 2. In terms of delivery performance, Factory 1 achieved an OTD of 91.66%, whereas Factory 2 reached 84.39%. While both factories need improvement for the forecast accuracy, and supplier A should share the area of corrective actions needed.

4.1.2 Supplier B Forecasting and OTD Performance

This section presents the results and analysis of forecasting performance from Factory 1 and Factory 2, and supplier B OTD performance at Factory 1 in Finland and Factory 2 in Italy. Subsequently, the relationship between forecasting accuracy and delivery performance at both sites is analysed, with a detailed description of the evaluation methods.

1. Supplier B Forecasting Performance for Factory 1 (Finland)

Table 8: MAPE Calculation for Supplier B (Factory 1, Finland)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $ A_t - F_t / A_t$
Feb-25	139	156	17	17	10.90%
Mar-25	111	131	20	20	15.27%
Apr-25	57	60	3	3	5.00%
May-25	79	98	19	19	19.39%
Jun-25	136	173	37	37	21.39%
Jul-25	159	308	149	149	48.38%
Aug-25	162	216	54	54	25.00%
Sep-25	176	199	23	23	11.56%
Oct-25	194	230	36	36	15.65%
Nov-25	180	192	12	12	6.25%
Dec-25	245	233	-12	12	5.15%
Jan-26	113	173	60	60	34.68%
Total / Average	1751	2169	418	442	MAPE = 18.22%

The forecast accuracy calculations are presented below for Factory 1:

Σ Forecasting Demand = 1751

Σ Actual Demand = 2169

Forecast Bias = $(1751 - 2169) / 2169 \times 100 = -19.27\%$

Forecast Consumption = $2169 / 1751 \times 100 = 123.87\%$.

MAPE is the arithmetic average of the 12 monthly APE%, MAPE = 18.22%

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(33258 / 12)} = 52.65$

Table 9: Supplier A OTD Performance (Factory 1, Finland)

Metric	Value
Σ Forecasting Demand	1751
Σ Actual Order Quantity	2169
Σ Delivered Quantity	2073
Overall OTD%	95.57%

Tables 8 and 9 show that for Supplier B, factory 1 received acceptable forecasting performance, but delivery performance is at the target level. The forecast bias is -19,27%,

which means forecast demand is lower than actual demand. This shows an under-forecasting pattern. In addition, the forecast consumption is 123,87%, which indicates that actual demand is higher than the forecast. The MAPE is 18.22%, which indicates acceptable forecasting accuracy because it is below 20%. The RMSE is 52,65, which reflects forecast error in unit terms. This indicates that forecast planning is not stable throughout the period. At the same time, the overall OTD is 95,57%, which is below the target level. The OTD target was 98% until 2025, and from 2026 onward, the target is 99%. Therefore, the results suggest that under-forecasting may have contributed to weak delivery performance. Therefore, this impacted the forecast and increased the risk of material shortages, urgent replenishment needs, production disruptions, delivery delays, and service-level risks. Overall, Factory 1 needs better forecast planning for Supplier B to improve OTD performance.

2. Supplier B Forecasting and OTD Performance for Factory 2 (Italy)

Table 10: MAPE Calculation for Supplier B (Factory 2, Italy)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $ A_t - F_t / A_t$
Feb-25	4580	4426	-154	154	3.48%
Mar-25	4490	4284	-206	206	4.81%
Apr-25	4461	3943	-518	518	13.14%
May-25	2098	2118	20	20	0.94%
Jun-25	2123	2155	32	32	1.48%
Jul-25	2943	2943	0	0	0.00%
Aug-25	1271	1131	-140	140	12.38%
Sep-25	3110	3146	36	36	1.14%
Oct-25	2570	2744	174	174	6.34%
Nov-25	4406	4288	-118	118	2.75%
Dec-25	1634	1770	136	136	7.68%
Jan-26	2190	2276	86	86	3.78%
Total / Average	35876	35224	-652	1620	MAPE = 4.83%

The forecast accuracy calculations are presented below for Factory:

Σ Forecasting Demand = 35876

Σ Actual Demand = 35224.

Forecast Bias = $(35876 - 35224) / 35224 \times 100 = +1.85\%$

Forecast Consumption = $35224 / 35876 \times 100 = 98.18\%$.

MAPE is the arithmetic average of the 12 monthly APE%, MAPE = 4.83%.

RMSE = $\sqrt{(\sum(A_t - F_t)^2/n)} = \sqrt{(426888/12)} = 188.61$

Table 11: Supplier B OTD Performance (Factory 2, Italy)

Metric	Value
Σ Forecasting Demand	35876
Σ Actual Order Quantity	35224
Σ Delivered Quantity	30357
Overall OTD%	86.18%

Tables 10 and 11 show that Supplier B receives good forecasts from Factory 2 (Italy), but OTD does not meet the target. Table 10 shows a MAPE of 4.83% and an RMSE of 188.61, indicating excellent forecast accuracy with moderate unit deviation. A forecast bias of +1.85% and forecast consumption of 98.18% show the forecast aligns closely with actual orders, with slight over-forecasting. Table 11 records an OTD of 86.18%, well below the target. These results indicate that poor OTD is likely due to supplier delivery execution issues rather than forecasting quality. Factory 2 should keep its current forecasting process for Supplier B, and Supplier B should develop a plan to improve delivery execution.

3. Comparative Analysis of Supplier A for Factory 1 and Factory 2

Table 12: Supplier B Forecasting and OTD Performance Comparison (Factory 1 vs Factory 2)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 1 (Finland)	18.22%	52.65	-19.27%	123.87%	95.67%	Shortage, Urgent replenishment
Factory 2 (Italy)	4.83%	188.61	+1.85	98.18%	86.18%	Material availability

Table 12 and Figure 9 indicate that Supplier B performed differently at Factory 1 and Factory 2. Factory 2 had good forecasting, with an MAPE of 4.83% compared to 18.22% at Factory 1, showing its forecasts are more accurate. In addition, Factory 2 kept its forecasts close to actual results, with a forecast bias of +1.85% and Forecast Consumption of

98.18%. On the other hand, Factory 1 tended to under-forecast, shown by a forecast bias of -19.27% and forecast consumption of 123.87%. Despite this, Factory 1 had a higher OTD rate of 95.57%, while Factory 2 had an OTD rate of 86.18%; the OTD trend is shown in Figure 9. These findings recommend that Factory 1 should improve its forecasting accuracy to improve supplier B delivery performance. Whereas Supplier B should develop their supply chain and capability planning to improve delivery performance, given their strong forecasting from Factory 2.

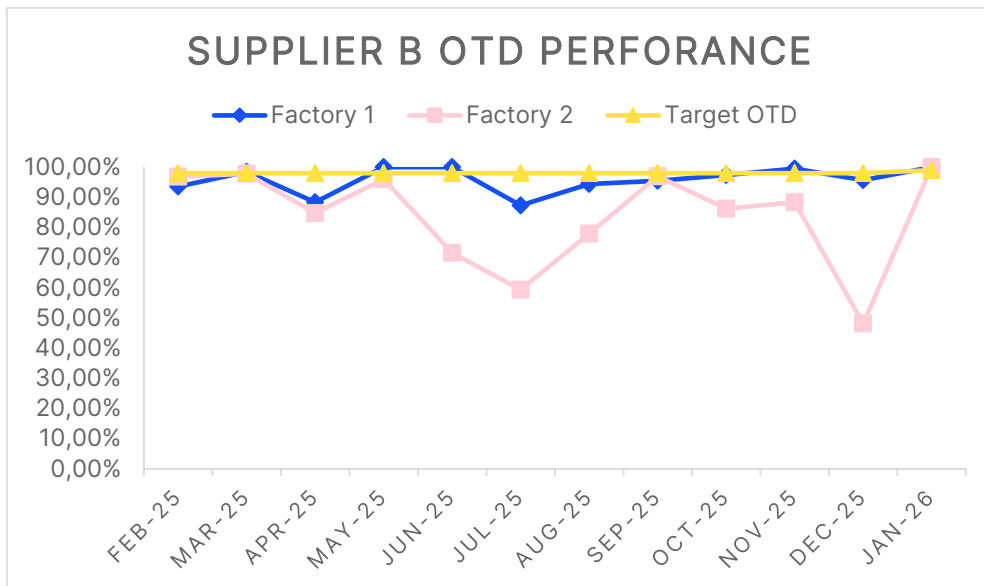


Figure 9: Comparison of Supplier B OTD Performance in Factory 1 and Factory 2

4.1.3 Supplier C Forecasting and OTD Performance

This section shows the results and analysis of Supplier C forecasting accuracy and On-time delivery (OTD) performance at Factory 1 in Finland and Factory 2 in Italy. First, it compares forecasting deviations with delivery performance at both factories. Next, it highlights performance patterns at each site and explains the next steps to address the identified deviations.

1. Supplier C Forecasting and OTD Performance for Factory 1

Table 13: MAPE Calculation for Supplier C (Factory 1, Finland)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $ A_t - F_t / A_t$
Feb-25	823	832	9	9	1.08%
Mar-25	807	807	0	0	0.00%
Apr-25	917	952	35	35	3.68%
May-25	451	1060	609	609	57.45%
Jun-25	612	637	25	25	3.92%
Jul-25	640	670	30	30	4.48%
Aug-25	816	827	11	11	1.33%
Sep-25	991	1003	12	12	1.20%
Oct-25	873	1348	475	475	35.24%
Nov-25	678	678	0	0	0.00%
Dec-25	495	495	0	0	0.00%
Jan-26	433	1342	909	909	67.73%
Total / Average	8536	10651	2115	2115	MAPE = 14.68%

The forecast accuracy calculations are presented below for Factory 1:

Σ Forecasting Demand = 8536

Σ Actual Demand = 10651

Forecast Bias = $(8536 - 10651) / 10651 \times 100 = -19.86\%$

Forecast Consumption = $10651 / 8536 \times 100 = 124.78\%$.

MAPE is the arithmetic average of the 12 monthly APE%, MAPE = 14.68%

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(1425883 / 12)} = 344.71$

Table 14: Supplier C OTD Performance (Factory 1, Finland)

Metric	Value
Σ Forecasting Demand	8103
Σ Actual Order Quantity	10651
Σ Delivered Quantity	8575
Overall OTD%	80.51%

Tables 13 and 14 show that Supplier C received acceptable forecasting accuracy at Factory 1 (Finland), but OTD remained well below the target. Table 13 lists a MAPE of 14.68%, indicating the forecast is good, and an RMSE of 344.71, which shows the average size of

forecast errors. The forecast bias of -19.86% and forecast consumption of 124.78% point to a steady pattern of under-forecasting, with actual demand exceeding expectations. Table 14 shows an overall OTD of 80.51%, well below the company goal. These results show that under-forecasting led to poor delivery performance by increasing the risk of shortages and urgent restocking. Improving OTD in Factory 1 will require more accurate and stable forecasts. However, supplier C could improve other issues to improve delivery performance, as Factory 1 already has good forecasting accuracy.

2. Supplier C Forecasting and Delivery Performance for Factory 2

Table 15: MAPE Calculation for Supplier C (Factory 2, Italy)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $ A_t - F_t / A_t$
Apr-25	1812	979	-833	833	85.09%
May-25	3976	621	-3355	3355	540.26%
Jun-25	6176	469	-5707	5707	1216.63%
Jul-25	9386	635	-8751	8751	1378.11%
Aug-25	1812	2302	490	490	21.29%
Sep-25	4548	5013	465	465	9.28%
Oct-25	6728	6456	-272	272	4.21%
Nov-25	7168	7890	722	722	9.15%
Dec-25	5804	4628	-1176	1176	25.41%
Jan-26	8112	6241	-1871	1871	29.98%
Feb-26	8772	8712	-60	60	0.69%
Mar-26	10080	9118	-962	962	10.55%
Total / Average	74374	53064	-21310	24664	MAPE = 277.57%

The forecast accuracy calculations are presented below for Factory 2:

$$\Sigma \text{Forecasting Demand} = 74374$$

$$\Sigma \text{Actual Demand} = 53064$$

$$\text{Forecast Bias} = (74374 - 53064) / 53064 \times 100 = +40.16\%$$

$$\text{Forecast Consumption} = 53064 / 74374 \times 100 = 71.35\%$$

MAPE is the arithmetic average of the 12 monthly APE%, MAPE = 277.57%

$$\text{RMSE} = \sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(127964018 / 12)} = 3265.53$$

Table 16: Supplier C OTD Performance (Factory 2, Italy)

Metric	Value
ΣForecasting Demand	74374
ΣActual Order	53064
ΣDelivered Quantity	35421
Overall OTD%	66.75%

Tables 15 and 16 show that Supplier C received poor forecasting from Factory 2 (Italy), and their delivery performance is very poor. Table 15 reports an MAPE of 277.57% and an RMSE of 3265.53, indicating highly inaccurate and volatile forecast performance from factory 2. A forecast bias of +40.16% and forecast consumption of 71.35% indicate clear over-forecasting, with predictions far exceeding actual demand. Large deviations in May-25, Jun-25, Jul-25, and Jan-26 further highlight the instability of the forecasts. Table 16 shows the OTD of 66.75%, which is well below the target. Poor forecasting led to planning inefficiencies, higher inventory risk, and irregular supplier demand. In that case, Factory 2 must improve forecasting accuracy to improve supplier delivery performance.

3. Comparative Analysis of Supplier C for Factory 1 and Factory 2

Table 17: Supplier C Forecasting and OTD Performance Comparison (Factory 1 vs Factory 2)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 1 (Finland)	14.68%	344.71	-19.86%	124.78%	80.51%	Shortage, urgent replenishment
Factory 2 (Italy)	277.57%	3265.53	+40.16%	71.35%	66.75%	Planning, inventory

Table 17 and Figure 10 illustrate the forecasting performance from Factory 1 and Factory 2, and supplier C OTD performance results. Factory 1 has better forecasting accuracy, with an MAPE of 14.68% and an RMSE of 344.71. Factory 2 has very poor forecasting accuracy recorded, with a much higher MAPE of 277.57% and an RMSE of 3265.53, indicating higher errors. Factory 1 consistently under-forecasts, with a bias of -19.86% and forecast consumption of 124.78%. Factory 2 over-forecast, with a bias of +40.16% and forecast consumption of 71.35%. Forecasting errors are much higher in Factory 2. The same trend appears in OTD, Factory 1 reached 80.51%, while Factory 2 reached 66.75% from supplier C, as shown in Figure 10. Factory 2 needs immediate improvement in forecasting due to larger errors that are likely to affect the supplier C delivery performance.

On the other hand, Supplier C should make a plan to improve delivery performance for Factory 1, as they shared a good forecast.

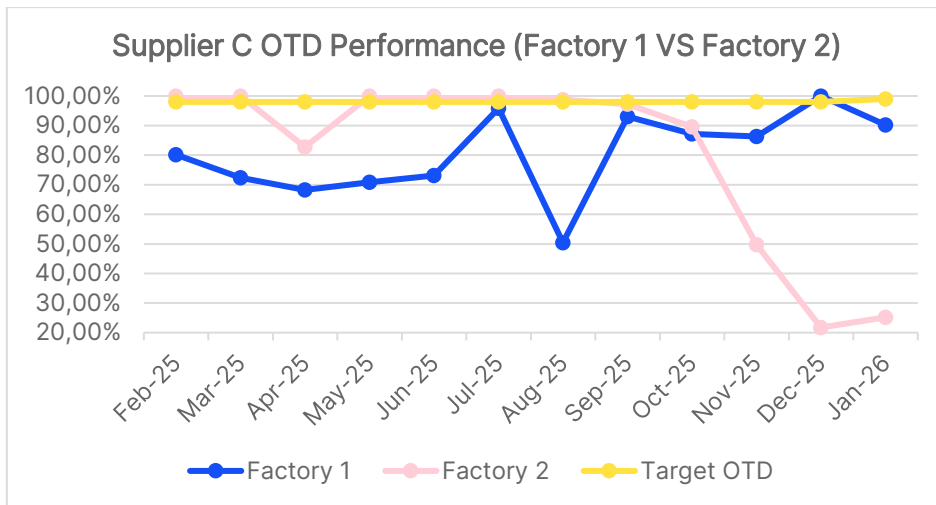


Figure 10: Supplier C OTD Performance for Factory 1 and Factory 2

4.1.4 Supplier D Forecasting and OTD Performance

This section presents the forecast performance of Factory 1 and Factory 2, as well as the delivery performance of supplier D to both factories. It evaluates forecast accuracy, forecast variability, and delivery to clarify the impact of forecasting on supplier D OTD.

1. Supplier D Forecasting and OTD Performance for Factory 1

Table 18: MAPE Calculation for Supplier D (Factory 1, Finland)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $\frac{ A_t - F_t }{A_t}$
Jan-25	230	368	138	138	37.50%
Feb-25	374	398	24	24	6.03%
Mar-25	204	318	114	114	35.85%
Apr-25	242	254	12	12	4.72%
May-25	210	263	53	53	20.15%
Jun-25	284	516	232	232	44.96%
Jul-25	250	404	154	154	38.12%
Aug-25	260	330	70	70	21.21%
Sep-25	302	328	26	26	7.93%
Oct-25	224	238	14	14	5.88%
Nov-25	102	114	12	12	10.53%
Dec-25	84	138	54	54	39.13%
Total / Average	2766	3669	903	903	MAPE = 22.67%

The forecast accuracy calculations are presented below for Factory 1:

Σ Forecasting Demand = 2766

Σ Actual Demand = 3669

Forecast Bias = $(2766 - 3669) / 3669 \times 100 = -24.61\%$

Forecast Consumption = $3669 / 2766 \times 100 = 132.65\%$.

MAPE is the arithmetic average of the 12 monthly APE%, MAPE = 22.50%

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(121941 / 12)} = 100,81$

Table 19: Supplier D OTD Performance (Factory 1, Finland)

Metric	Value
Σ Forecasting Demand	2766
Σ Actual Order Quantity	3669
Σ Delivered Quantity	3645
Overall OTD%	99.35%

Tables 18 and 19 show that Supplier D receives poor forecasting from factory 1 but good delivery reliability. A forecast bias of -24.61% and forecast consumption of 132.65% indicate consistent demand underestimation. MAPE of 22.67% and RMSE of 100.81 confirm inaccurate forecasts. Monthly data show that demand has consistently exceeded forecasts, indicating unstable planning. However, On-Time Delivery (OTD) reached 99.35%, above target, showing reliable deliveries despite forecast issues. Ongoing under-forecasting raises the risk of shortages, urgent replenishment, and planning instability. Factory 1 must improve forecasting accuracy for Supplier D to maintain a reliable supply.

2. Supplier D Forecasting and OTD Performance for Factory 2

Table 20: MAPE Calculation for Supplier D (Factory 2, Italy)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $ A_t - F_t / A_t$
Jan-25	212	242	30	30	12.40%
Feb-25	218	170	-48	48	28.24%
Mar-25	188	158	-30	30	18.99%
Apr-25	182	116	-66	66	56.90%
May-25	136	142	6	6	4.23%
Jun-25	136	130	-6	6	4.62%
Jul-25	179	150	-29	29	19.33%
Aug-25	75	52	-23	23	44.23%
Sep-25	162	186	24	24	12.90%
Oct-25	163	176	13	13	7.39%
Nov-25	176	198	22	22	11.11%
Dec-25	147	116	-31	31	26.72%
Total / Average	1974	1836	-138	328	MAPE = 20.59%

The forecast accuracy calculations are presented below for Factory 2:

Σ Forecasting Demand = 1974

Σ Actual Demand = 1836.

Forecast Bias = $(1974 - 1836) / 1836 \times 100 = +7.52\%$

Forecast Consumption = $1836 / 1974 \times 100 = 93.01\%$.

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(12092 / 12)} = 31,74$

Table 21: Supplier D OTD Performance (Factory 2, Italy)

Metric	Value
Σ Forecasting Demand	1964
Σ Actual Order Quantity	1836
Σ Delivered Quantity	1812
Overall OTD%	98.69%

Tables 20 and 21 show that Supplier D has acceptable forecasting from Factory 2, supporting good delivery performance. A forecast bias of +7.52% and forecast consumption of 93.01% indicate a tendency to over-forecast, with forecasted demand exceeding actual demand. The MAPE of 20.59% is slightly above the acceptable threshold. The RMSE

of 31.74 reflects the average forecast error in units. Although total forecast and actual orders were similar, some months showed significant discrepancies. The OTD is 98.69%, indicating consistently reliable delivery performance. Overall, Supplier D should maintain good delivery as Factory 2 has acceptable forecast accuracy to support good OTD.

3. Comparative Analysis of Supplier D for Factory 1 and Factory 2

Table 22: Supplier D Forecasting and OTD Performance from Factory 1 and Factory 2

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 1 (Finland)	22.67%	100.81	-24.61%	132.65%	99.35%	Shortage, Urgent replenishments
Factory 2 (Italy)	20.59%	31.74	+7.52%	93.01%	98.69%	Inventory Cost

Table 22 and Figure 11 show that Supplier D has poor forecasting performance from Factory 1 but acceptable from Factory 2. OTD remained consistently good in both settings. Factory 2 has good forecasting accuracy, with an MAPE of 20.59% and an RMSE of 31.74, compared to 22.67% and 100.81 in Factory 1. Factory 1 shows significant under-forecasting, with a forecast bias of -24.61% and forecast consumption of 132.65%, increasing the risk of shortages and planning instability. In contrast, Factory 2 showed slight over-forecasting, with a forecast bias of +7.52% and forecast consumption of 93.01%, which may cause excess planning and higher inventory costs. Despite these forecasting challenges in Factory 1, Supplier D OTD remained high across both factories, at 99.35% in Factory 1 and 98.69% in Factory 2. In summary, Factory 1 should improve its forecasting to achieve better OTD and avoid future risks.

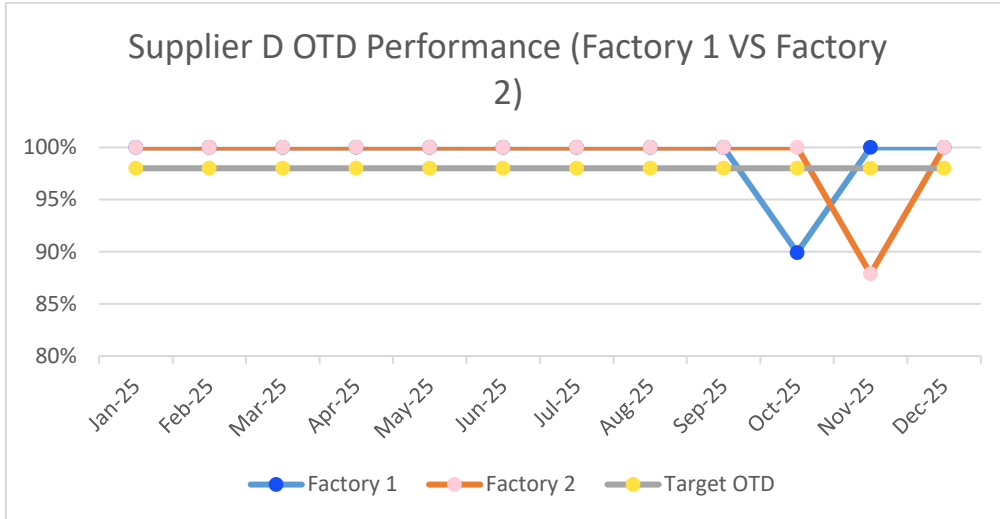


Figure 11: Supplier D OTD Performance for Factory 1 and Factory 2

4.1.5 Supplier E Forecasting and OTD Performance

This section presents the forecast performance of Factory 3, as well as the delivery performance of supplier E. It shows forecast accuracy, forecast variability, and delivery performance to understand how forecasting relates to on-time delivery in this factory.

Table 23: MAPE Calculation for Supplier E (Factory 3, Finland)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $ A_t - F_t / A_t$
Jan-25	647	630	-17	17	2.70%
Feb-25	594	540	-54	54	10.00%
Mar-25	672	515	-157	157	30.49%
Apr-25	629	658	29	29	4.41%
May-25	646	548	-98	98	17.88%
Jun-25	708	718	10	10	1.39%
Jul-25	797	1012	215	215	21.25%
Aug-25	497	411	-86	86	20.92%
Sep-25	727	517	-210	210	40.62%
Oct-25	727	630	-97	97	15.40%
Nov-25	669	627	-42	42	6.70%
Dec-25	646	462	-184	184	39.83%
Jan-26	534	438	-96	96	21.92%
Feb-26	466	467	1	1	0.21%
Mar-26	487	346	-141	17	40.75%
Total / Average	9446	8519	-927	1437	MAPE = 18.30%

The forecast accuracy calculations are presented below for Factory 3:

Σ Forecasting Demand = 9446

Σ Actual Order = 8519

Forecast Bias = $(9446 - 8519) / 8519 \times 100 = +10.88\%$

Forecast Consumption = $8519 / 9446 \times 100 = 90.19\%$.

MAPE is the arithmetic average of the 15 monthly APE%, MAPE = 18.30%

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(210247 / 15)} = 118.39$

Table 24: Supplier E OTD Summary (Factory 3, Finland)

Metric	Value
Σ Forecasting Demand	9446
Σ Actual Order Quantity	8519
Σ Delivered Quantity	6773
Overall OTD%	79.50%

Tables 23, 24, and 25 show that Supplier E has good forecasting performance from Factory 3, but delivery performance is below target. A forecast bias of +10.88% and forecast consumption of 90.19% indicate forecasts were higher than actual demand during the period. The MAPE of 18.30% shows good forecast accuracy, and the RMSE of 118.39 indicates a moderate difference between forecasted demand and actual orders. However, the overall OTD rate is well below the company 2025 goal of 98% and 2026 goal of 99%, as shown in Figure 12. These results show that forecasting performance is good, while delivery performance is weak. Slightly over-forecasting leads to planning problems, increased inventory risk, higher inventory levels, and reduced capacity. Therefore, Supplier E should make a plan to improve delivery reliability.

Table 25: Supplier E Forecasting and OTD Performance (Factory 3, Finland)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 3	18.30%	118.39	+10.88%	90.19%	79.50%	Planning inefficiency, excess inventory cost,

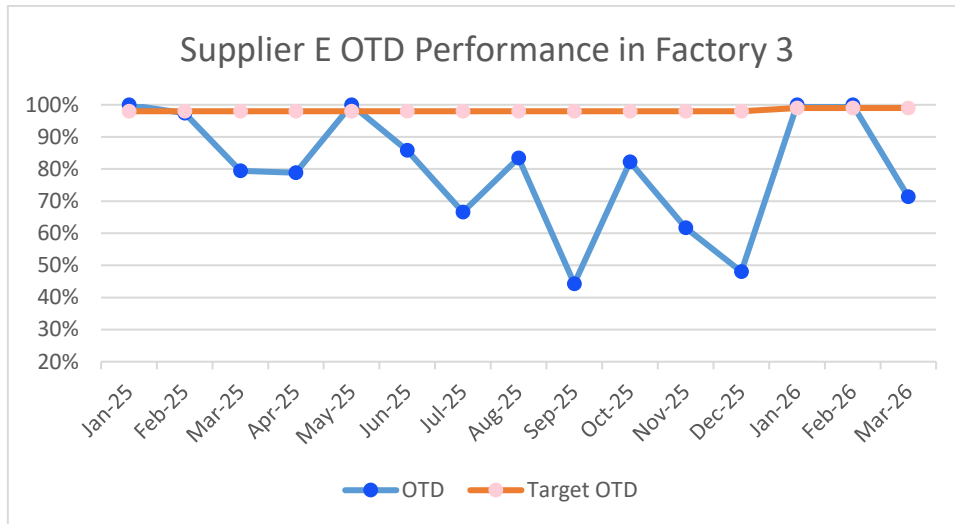


Figure 12: Supplier E OTD Performance for Factory 3

4.1.6 Supplier F Forecasting and OTD Performance

This section presents the forecast performance of Factory 3 and the delivery performance of supplier F. It shows forecast accuracy, variability, and delivery performance to explain how forecasting relates to on-time delivery in this factory. By assessing forecast accuracy, deviation, and OTD results, this section demonstrates the reliability of the forecasting process in supporting consistent deliveries.

Table 26: MAPE Calculation for Supplier F (Factory 3, Finland)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $\frac{ A_t - F_t }{A_t}$
Jan-25	2922	3617	695	695	19.21%
Feb-25	2802	2579	-223	223	8.65%
Mar-25	2621	3199	578	578	18.07%
Apr-25	2979	2765	-214	214	7.74%
May-25	2763	2855	92	92	3.22%
Jun-25	2952	3239	287	287	8.86%
Jul-25	3165	2568	-597	597	23.25%
Aug-25	3055	2669	-386	386	14.46%
Sep-25	3218	2606	-612	612	23.48%
Oct-25	3313	2918	-395	395	13.54%
Nov-25	2638	2488	-150	150	6.03%
Dec-25	1893	1195	-698	698	58.41%
Jan-26	2435	2030	-405	405	19.95%
Feb-26	1952	1608	-344	344	21.39%
Mar-26	1957	1931	-26	26	1.35%
Total Average /	40665	38267	-2398	5702	MAPE = 16.51

The forecast accuracy calculations are presented below for Factory 3:

Σ Forecasting Demand = 40665

Σ Actual Demand = 38267

Forecast Bias = $(40665 - 38267) / 38267 \times 100 = +6.27\%$

Forecast Consumption = $38267 / 40665 \times 100 = 94.10\%$.

MAPE is the arithmetic average of the 15 monthly APE%, MAPE = 16.51%.

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2/n)} = \sqrt{(2832182/15)} = 434.53$

Table 27: Supplier F OTD performance (Factory 3, Finland)

Metric	Value
Σ Forecasting Demand	40665
Σ Actual Order Quantity	38267
Σ Delivered Quantity	34898
Overall OTD%	91.20%

Table 26 shows forecast accuracy with a MAPE of 16.51%, an RMSE of 434.53, a forecast bias of +6.27%, and forecast consumption of 94.10% in Factory 3 in Finland. This good forecast performance, marked by over-forecasting, may increase exposure to excess inventory and require short-term planning adjustments. Table 27 shows Supplier F achieved an OTD rate of 91.20%, below the company target and the OTD trend in Figure 13. Table 28 suggests that good forecast performance did not support stable delivery. Overall, Supplier F should improve supplier planning to ensure on-time delivery and better OTD performance.

Table 28: Supplier F Forecasting and OTD Performance (Factory 3, Finland)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 3 (Finland)	16.51%	434.53	+6.27%	94.10%	91.20%	inventory

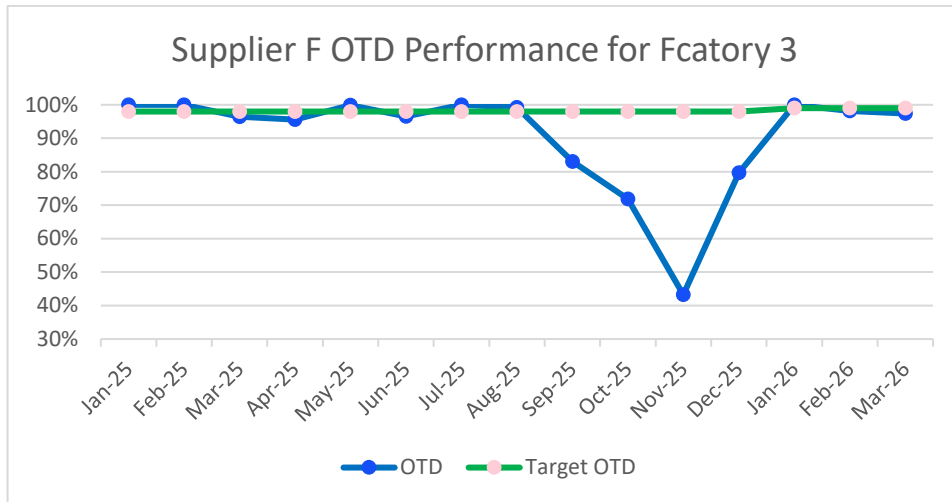


Figure 13: Supplier F OTD Performance for Factory 3

4.1.7 Supplier G Forecasting and OTD Performance

This subsection assesses the forecasting accuracy of Factory 1 in Finland and the delivery performance of supplier G. It also examines the relationship between forecasting metrics and supplier delivery performance. Table 29 presents detailed KPI calculations, while Table 30 provides the on-time delivery (OTD) summary. Table 31 summarises the integrated analysis of forecasting and delivery performance.

Table 29: MAPE Calculation for Supplier G (Factory 1, Finland)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $\frac{ A_t - F_t }{A_t}$
May-25	7439	22488	15049	15049	66.92%
Jun-25	9336	17800	8464	8464	47.55%
Jul-25	9556	22253	12697	12697	57.06%
Aug-25	8037	19689	11652	11652	59.18%
Sep-25	10162	11143	981	981	8.80%
Oct-25	8771	23798	15027	15027	63.14%
Nov-25	7765	16028	8263	8263	51.55%
Dec-25	8683	17655	8972	8972	50.82%
Jan-26	7690	13287	5597	5597	42.12%
Feb-26	8643	19538	10895	10895	55.76%
Mar-26	8643	18692	10049	10049	53.76%
Apr-26	8643	17160	8517	8517	49.63%
Total Average /	103368	221843	118132	118132	MAPE = 50.53%

The forecast accuracy calculations are presented below for Factory 1:

$$\Sigma \text{Forecasting Demand} = 103368$$

Σ Actual Demand = 219531

Forecast Bias = $(103368 - 219531) / 219531 \times 100 = -52.91\%$

Forecast Consumption = $219531 / 103368 \times 100 = 212.38\%$.

MAPE is the arithmetic average of the 12 monthly, MAPE = 50.53%

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(1294190777 / 12)} = 10385.05$

Table 30: Supplier G OTD Summary (Factory 1, Finland)

Metric	Value
Σ Forecasting Demand	103368
Σ Actual Order Quantity	219531
Σ Delivered Quantity	179503
Overall OTD%	81.77%

Table 29 shows that Supplier G had a MAPE of 50.53%, an RMSE of 10,385.05, a forecast bias of -52.91%, and forecast consumption of 212.38%. These results indicate poor forecast performance at factory 1, which in turn leads to poor delivery performance by Supplier G, mainly due to consistent under-forecasting. This underestimation can lead to material shortages, urgent replanning, and increased pressure to expedite orders when actual demand is much higher than forecast. The poor forecast performance results in a delivery performance of 81.77%, well below the company target shown in Table 30. Figure 14 illustrates the OTD trend over time. Together with Table 31, these results suggest that weak forecasts caused unstable deliveries, urgent restocking, and a higher risk of production disruptions.

Table 31: Supplier G Forecasting and OTD Performance (Factory 1, Finland)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 1 (Finland)	50.53%	10385	-52.91%	212.38%	81.77%	Urgent replenishment, production disruption

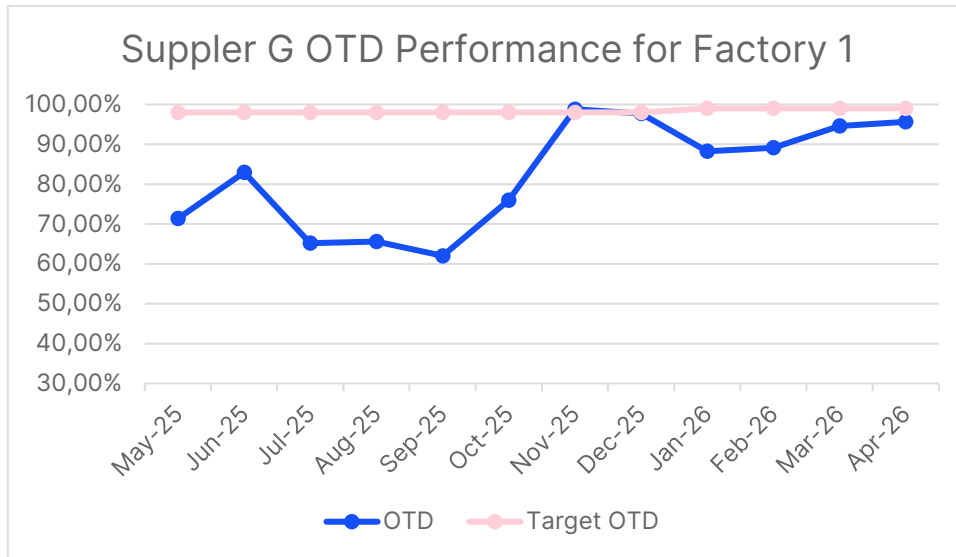


Figure 14: Supplier G OTD Performance for Factory 1

4.1.8 Supplier H Forecasting and OTD Performance

This part presents the results and analysis of forecasting accuracy from factory 2 and On-Time Delivery performance from supplier H. Table 32 shows KPI calculations. Table 33 provides the OTD summary. Table 34 summarises overall forecasting and delivery performance.

Table 32: MAPE Calculation for Supplier H (Factory 2, Italy)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $\frac{ A_t - F_t }{A_t}$
Feb-25	25836	25776	-60	60	0.23%
Mar-25	24738	25243	505	505	2.00%
Apr-25	25498	26528	1030	1030	3.88%
May-25	20792	21793	1001	1001	4.59%
Jun-25	21698	22978	1280	1280	5.57%
Jul-25	27834	28384	550	550	1.94%
Aug-25	4040	12561	8521	8521	67.84%
Sep-25	19402	28171	8769	8769	31.13%
Oct-25	21084	14668	-6416	6416	43.74%
Nov-25	17014	20526	3512	3512	17.11%
Dec-25	11474	12556	1082	1082	8.62%
Jan-26	26972	15372	-11600	11600	75.46%
Total Average /	246382	254556	8174	44326	MAPE = 21.84%

The forecast accuracy calculations are presented below for Factory 2:

$$\Sigma \text{Forecasting Demand} = 246382$$

Σ Actual Order = 254556

Forecast Bias = $(246382 - 254556) / 254556 \times 100 = -0.03\%$

Forecast Consumption = $254556 / 246382 \times 100 = 103.32\%$

MAPE is the arithmetic average of the 12 monthly APE%, MAPE = 21.84%

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(342995152 / 12)} = 5346.301$

Table 33: Supplier H OTD Performance (Factory 2, Italy)

Metric	Value
Σ Forecasting Demand	246382
Σ Actual Order Quantity	254556
Σ Delivered Quantity	198745
Overall OTD%	64.22%

Table 32 shows that factory 2 has a MAPE of 21.84%, an RMSE of 5,346.301, a forecast bias of -0.03%, and forecast consumption of 103.32%. These metrics show that total forecasted demand closely matched actual orders, and forecast accuracy is just above 20%. Table 33 indicates that Supplier H achieved an overall OTD rate of 64.22%, which is well below the company target. The monthly OTD trend is shown in Figure 15. Table 34 shows that weak OTD performance correlated with both forecasting instability and supply-related constraints. Supplier H, based in China, supplies Factory 2 in Italy. The extended supply route likely increases the risk of delays and limits delivery flexibility. Geopolitical and trade-related disruptions may also impact the supply process. This performance profile introduces risks related to delays, service levels, production continuity, and material availability.

Table 34: Supplier H Forecasting and OTD Performance (Factory 2, Italy)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Average OTD%	Risk
Factory 2 (Italy)	21.84%	5346	-0.03%	103.32%	64.22%	Long supply Chain

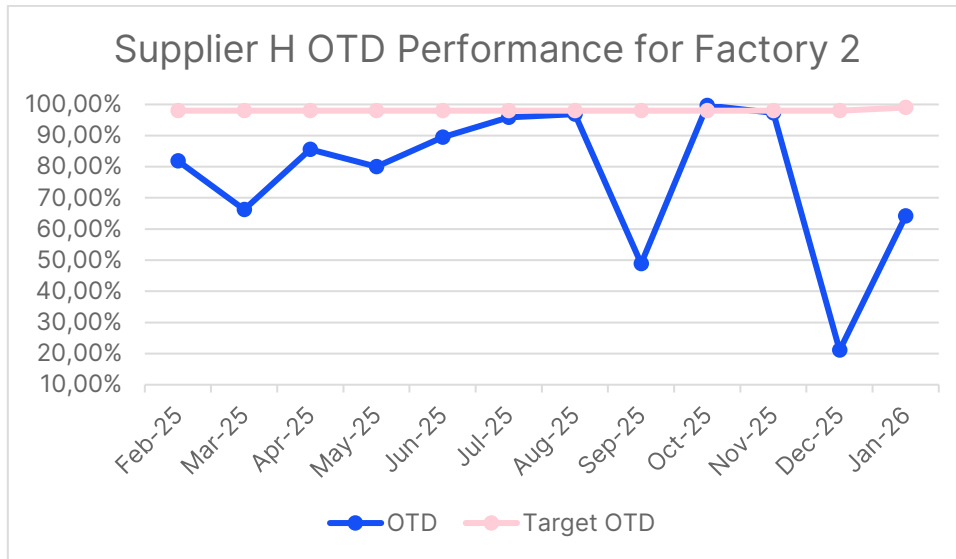


Figure 15: Supplier H OTD Performance for Factory 2

4.1.9 Supplier I Forecasting and OTD Performance

This section assesses forecasting accuracy from factory 2 and reviews delivery performance of supplier I. Table 35 presents the forecast performance numbers, while Table 36 summarizes the on-time delivery results. Finally, Table 37 provides an overall explanation.

Table 35: MAPE Calculation for Supplier I (Factory2, Italy)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $\frac{ A_t - F_t }{A_t}$
Jan-25	40198	32701	-7497	7497	22.93%
Feb-25	44893	39824	-5069	5069	12.73%
Mar-25	38443	44145	5702	5702	12.92%
Apr-25	43160	42803	-357	357	0.83%
May-25	39452	28143	-11309	11309	40.18%
Jun-25	42766	41907	-859	859	2.05%
Jul-25	43425	68233	24808	24808	36.36%
Aug-25	26923	16522	-10401	10401	62.95%
Sep-25	43015	48414	5399	5399	11.15%
Oct-25	42672	35029	-7643	7643	21.82%
Nov-25	44108	38020	-6088	6088	16.01%
Dec-25	25837	30269	4432	4432	14.64%
Total Average /	474892	466010	-8882	89564	MAPE = 21.21%

The forecast accuracy calculations are presented below for Factory 2:

Σ Forecasting Demand = 474892

Σ Actual Order = 466010

Forecast Bias = $(474892 - 466010) / 466010 \times 100 = +1.91\%$

Forecast Consumption = $466010 / 474892 \times 100 = 98.13\%$.

MAPE is the arithmetic average of the 12 monthly APE%, MAPE = 21.21%.

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(1111060068 / 12)} = 9622.28$

Table 36: Supplier I OTD Summary (Factory2, Italy)

Metric	Value
Σ Forecasting Demand	474892
Σ Actual Order Quantity (Meter)	466010
Σ Delivered Quantity (Meter)	460989
Overall OTD%	98.92%

Table 35 shows that factory 2 has a MAPE of 21.21%, an RMSE of 9,622.28, a forecast bias of +1.91%, and forecast consumption of 98.13%. These results mean the forecasted demand mostly matched actual orders, though accuracy varied over time. Table 36 reports an overall on-time delivery rate of 98.92% for Supplier I, close to the company target. Figure 16 shows the trend in monthly on-time delivery performance. Table 37 indicates that despite changes in forecasting performance, Supplier I maintained good delivery reliability. However, Factory 2 should improve its forecasting accuracy to ensure good supplier performance.

Table 37: Supplier I Forecasting and OTD Performance (Factory 2, Italy)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Average OTD%	Risk
Factory 2 (Italy)	21.21%	9622	+1.91%	98.13%	98.92%	Low risk to OTD, while volatile forecast

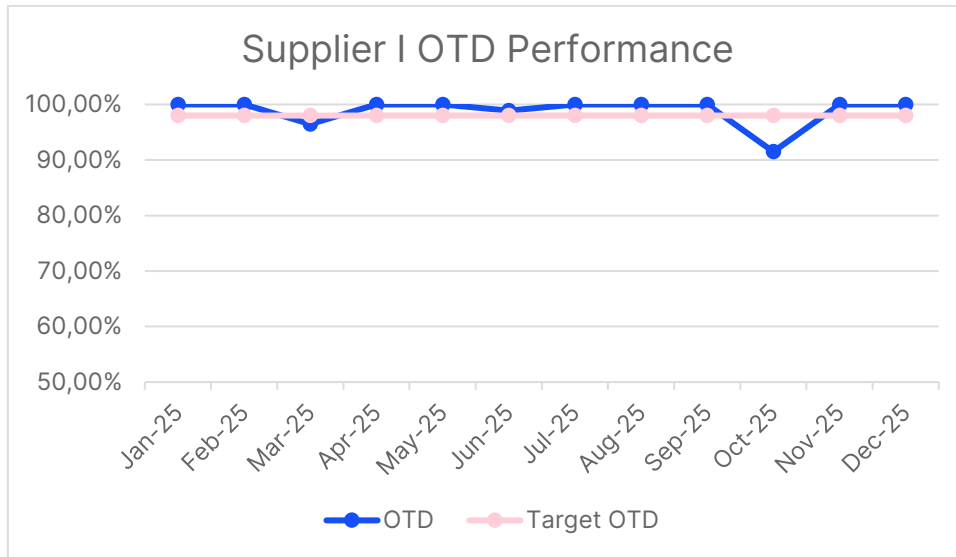


Figure 16: Supplier I OTD Performance for Factory 2

4.1.10 Supplier J Forecasting and OTD Performance

This section presents the results and analysis of forecasting accuracy from factory 4 and On-Time Delivery (OTD) performance from Supplier J at Factory 4 in the Czech Republic. To begin, Table 38 lists the KPI calculations. Next, Table 39 summarizes the OTD results. Finally, Table 40 brings together the findings from both forecasting and delivery performance.

Table 38: MAPE Calculation for Supplier J (Factory 4, Czech Republic)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $ A_t - F_t / A_t$
Sep-25	95397	67790	-27607	27607	40.72%
Oct-25	103174	79786	-23388	23388	29.31%
Nov-25	86349	98697	12348	12348	12.51%
Dec-25	67352	79513	12161	12161	15.30%
Jan-26	89433	70621	-18812	18812	26.64%
Feb-26	93011	78201	-14810	14810	18.94%
Mar-26	103242	121439	18197	18197	14.98%
Apr-26	110469	104303	-6166	6166	5.91%
Total / Average	748427	700350	-48077	133489	MAPE = 20.54%

The forecast accuracy calculations are presented below for Factory 4:

Σ Forecasting Demand = 748427

Σ Actual Order = 700350

Forecast Bias = $(748427 - 700350) / 700350 \times 100 = +6,86\%$

Forecast Consumption = $700350 / 748427 \times 100 = 93.58\%$.

MAPE is the arithmetic average of the 8 monthly APE%, MAPE = 20.54%

RMSE = $\sqrt{(\sum(A_t - F_t)^2 / n)} = \sqrt{(2551885827 / 8)} = 17860.17$

Table 39: Supplier J OTD Summary (Factory 4, Czech Republic)

Metric	Value
Σ Forecasting Demand	748427
Σ Actual Order Quantity	700350
Σ Delivered Quantity	697458
Overall OTD%	99.59%

Table 38 shows that factory 4 has an MAPE of 20.54%, an RMSE of 17,860.17, a forecast bias of +6.86%, and a forecast consumption of 93.58%. These indicate acceptable forecast accuracy from factory 4, with moderate over-forecasting. Forecasted demand consistently exceeded actual orders. Overall, forecasting performance is acceptable, though monthly variation persisted. In contrast, Table 39 shows Supplier J's OTD rate reached 99.59%, surpassing the company target of 98% by 2025 and 99% from 2026. Figure 17 shows the OTD trend. Comparison of Tables 38, 39, and 40 shows Supplier J maintained excellent delivery despite forecast variation. Table 40 emphasises forecast stability and risks of inventory inefficiency from over-forecasting, indicating delivery concerns. Factory 4 should focus on improving forecast accuracy, and Supplier J should maintain strong OTD performance.

Table 40: Supplier J Forecasting and OTD Performance (Factory 4, Czech Republic)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 4	20.54%	17860.17	+6.86%	93.58%	99.59%	Planning instability

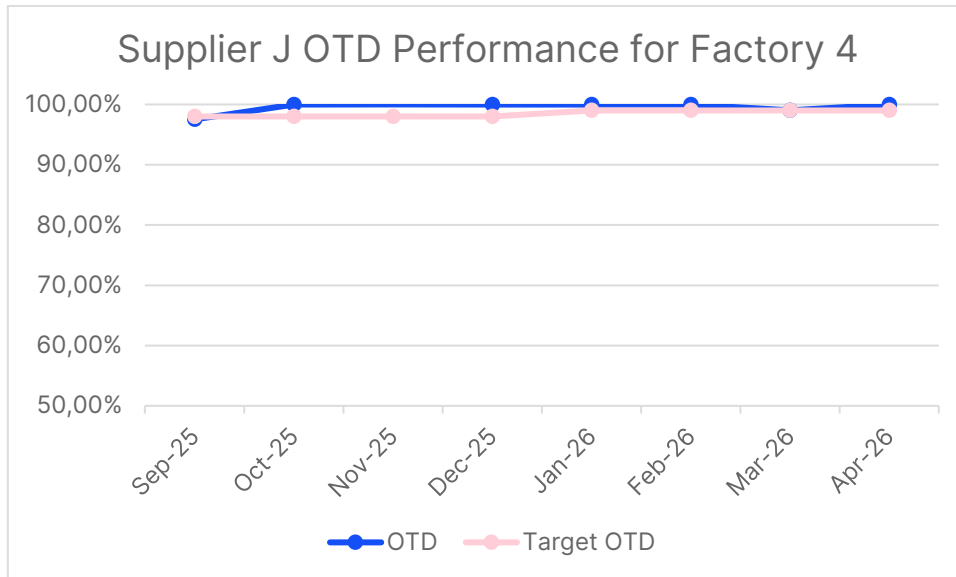


Figure 17: Supplier J OTD Performance for Factory 4

4.1.11 Supplier K Forecasting and OTD Performance

This part evaluates Supplier K forecasting and OTD performance at Factory 4 in the Czech Republic. Forecast accuracy is measured by MAPE, RMSE, forecast bias, and forecast consumption, and compared to delivery performance. Table 40 shows KPI calculations, Table 41 summarizes OTD results, and Table 42 integrates the findings.

Table 41: MAPE Calculation for Supplier K (Factory 4, Czech Republic)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $ A_t - F_t / A_t$
Sep-25	57285	41785	-15500	15500	37.09%
Oct-25	61210	63647	2437	2437	3.83%
Nov-25	51228	54675	3447	3447	6.31%
Dec-25	37433	37299	-134	134	0.36%
Jan-26	47550	43263	-4287	4287	9.91%
Feb-26	48482	48496	14	14	0.03%
Mar-26	52652	62187	9535	9535	15.33%
Apr-26	50439	64910	14471	14471	22.30%
Total Average /	406279	416262	9983	49825	MAPE = 11.89%

The forecast accuracy calculations are presented below for Factory 4:

Σ Forecasting Demand = 406279

Σ Actual Order = 416262

Forecast Bias = $(406279 - 416262) / 416262 \times 100 = -2.40\%$

Forecast Consumption = $416262 / 406279 \times 100 = 102.46\%$.

MAPE is the arithmetic average of the 8 monthly APE%, MAPE = 11.89%

RMSE = $\sqrt{(\sum(A_t - F_t)^2 / n)} = \sqrt{(576793365 / 8)} = 8491.12$

Table 42: Supplier K OTD Performance (Factory 4, Czech Republic)

Metric	Value
Σ Forecasting Demand	406279
Σ Actual Order Quantity	416262
Σ Delivered Quantity	415549
Overall OTD%	99.83%

Table 41 shows that factory 4 has a MAPE of 11.89%, an RMSE of 8,491.12, a forecast bias of -2.40%, and forecast consumption of 102.46%. These metrics demonstrate good forecast accuracy and a slight tendency to underforecast, indicating actual orders were marginally higher than forecast demand. Forecast performance is good, with some monthly variation remaining. Supplier K achieved an overall On-Time Delivery (OTD) rate of 99.83%, above company targets. The OTD trend is shown in Figure 18. Comparing forecast results in Table 41 and delivery results in Table 42, as summarised in Table 43, confirms Supplier K consistently excelled in delivery performance, and Factory 4 had a very good forecast. Factory 4 should continue its current forecasting approach and sustain the high OTD performance.

Table 43: Supplier K Forecasting and OTD Performance (Factory 4, Czech Republic)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 4	11.89%	8491.12	-2.40%	102.46%	99.39%	Minor planning inefficiency

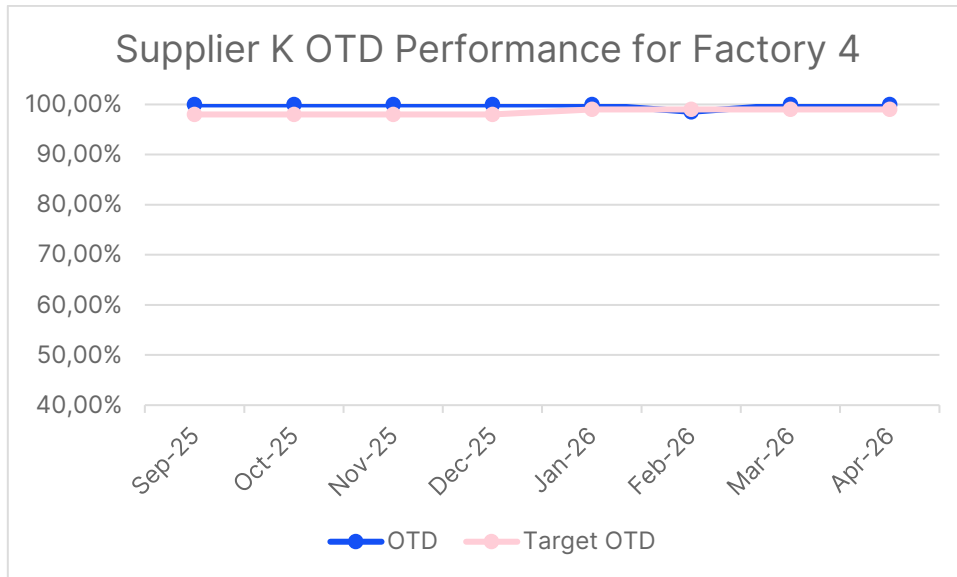


Figure 18: Supplier K OTD Performance for Factory 4

4.1.12 Supplier L Forecasting and OTD Performance

This part assesses forecasting accuracy for Factory 4 in the Czech Republic and OTD performance for Supplier L. It examines how forecasting accuracy and OTD performance relate to each other and how both impact supplier delivery. Table 44 details KPI calculations, Table 45 summarises OTD results, and Table 46 integrates forecasting insights with delivery outcomes.

Table 44: MAPE Calculation for Supplier L (Factory 4, Czech Republic)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $\frac{ A_t - F_t }{A_t}$
Oct-25	5960	27540	21580	21580	78.36%
Nov-25	31953	22191	-9762	9762	43.99%
Dec-25	21358	19732	-1626	1626	8.24%
Jan-26	32312	39869	7557	7557	18.95%
Feb-26	34928	36603	1675	1675	4.58%
Mar-26	43928	46885	2957	2957	6.31%
Apr-26	62415	39362	-23053	23053	58.57%
Total / Average	232854	232182	-672	68110	MAPE = 31.28%

The forecast accuracy calculations are presented below for Factory 4:

Σ Forecasting Demand = 232854

Σ Actual Order = 232182

Forecast Bias = $(232854 - 232182) / 232182 \times 100 = +0,29\%$

Forecast Consumption = $232182 / 232854 \times 100 = 99.71\%$.

MAPE is the arithmetic average of the 7 monthly APE%, MAPE = 31.28%

RMSE = $\sqrt{(\sum(A_t - F_t)^2/n)} = \sqrt{(1163735452/7)} = 12893.716$

Table 45: Supplier L OTD Performance (Factory 4, Czech Republic)

Metric	Value
Σ Forecasting Demand	232854
Σ Actual Order Quantity	232182
Σ Delivered Quantity	197534
Overall OTD%	85.08%

Table 44 shows that factory 4 has a MAPE of 31.28%, an RMSE of 12,893.716, a forecast bias of +0.29%, and forecast consumption of 99.71%, all indicating poor forecast accuracy. While the total forecast volume closely matched the actual order volume, significant monthly variation persisted. Overall, the data indicate unstable forecasting performance throughout the analysis period. Table 45 shows that Supplier L achieved an overall OTD rate of 85.08%, below the company target of 98% until 2025 and 99% from 2026 onward. The OTD trend is shown in Figure 19. Comparing the forecasting results in Table 44 and delivery outcomes in Table 44, as summarised in Table 46, reveals weak forecast performance from factory 4 and low delivery reliability from supplier L. To mitigate delivery risks, Factory 4 should focus on improving forecast stability for Supplier L. Meanwhile, supplier L should create an improvement plan to increase OTD performance.

Table 46: Supplier L Forecasting and OTD Performance (Factory 4, Czech Republic)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD	Risk
Factory 4 (Czech Republic)	31.28%	12893.716	+0.29%	99.71%	85.08%	Planning instability, inventory risk

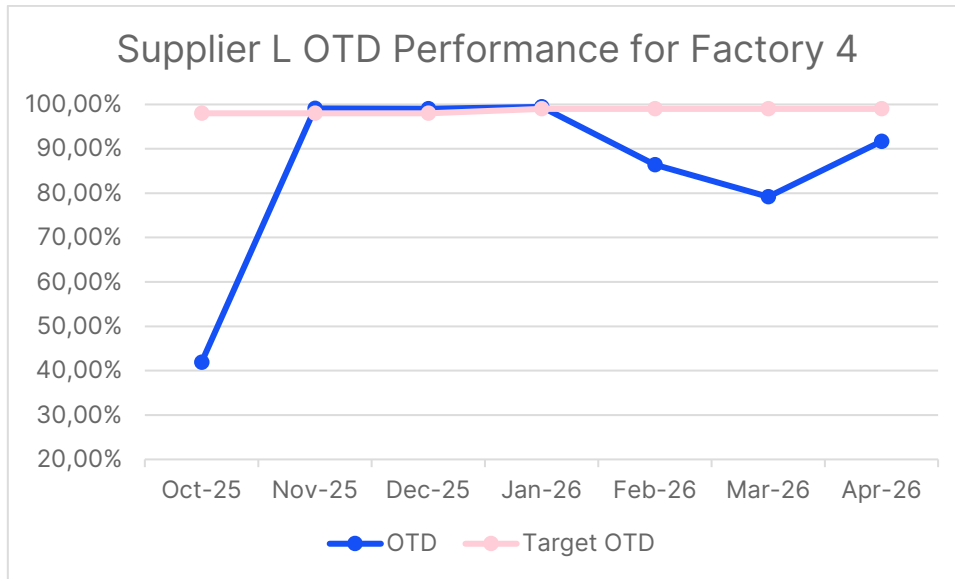


Figure 19: Supplier L OTD Performance for Factory 4

4.1.13 Supplier M Forecasting and OTD Performance

This part evaluates factory forecasting accuracy and supplier M delivery performance. Table 47 presents the MAPE calculations. Table 48 summarises supplier M OTD results. Table 49 provides an integrated explanation of both forecasting accuracy and delivery performance.

Table 47: MAPE Calculation for Supplier M (Factory 2, Italy)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $\frac{ A_t - F_t }{A_t}$
Feb-25	75118	61582	-13536	13536	21.98%
Mar-25	70199	55960	-14239	14239	25.45%
Apr-25	69988	90378	20390	20390	22.56%
May-25	71932	50987	-20945	20945	41.08%
Jun-25	70546	57538	-13008	13008	22.61%
Jul-25	71966	108699	36733	36733	33.79%
Aug-25	43838	51823	7985	7985	15.41%
Sep-25	68227	62640	-5587	5587	8.92%
Oct-25	68255	75749	7494	7494	9.89%
Nov-25	70166	81052	10886	10886	13.43%
Dec-25	42624	37274	-5350	5350	14.35%
Jan-26	68104	63233	-4871	4871	7.70%
Total Average	790963	796915	5952	161024	MAPE = 19.76%

The forecast accuracy calculations are presented below for Factory 2:

Σ Forecasting Demand = 790963

Σ Actual Order Quantity = 796915

Forecast Bias = $(790963 - 796915) / 796915 \times 100 = -0.75\%$

Forecast Consumption = $796915 / 790963 \times 100 = 100.75\%$.

MAPE is the arithmetic average of the 12 monthly APE%, MAPE = 19.76%

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(3080927862 / 12)} = 16023,23$

Table 48: Supplier M OTD Performance (Factory 2, Italy)

Metric	Value
Σ Forecasting Demand	790963
Σ Actual Order Quantity	796915
Σ Delivered Quantity	793541
Overall OTD%	99.58%

Table 47 shows that factory 2 has an MAPE of 19.76%, an RMSE of 16023.23, a forecast bias of -0.75% , and forecast consumption of 100.75%. These results indicate acceptable forecasting performance, with forecasted demand slightly below actual orders. The MAPE suggests adequate accuracy. The RMSE highlights significant monthly deviations. Forecast performance was not fully stable. The largest errors occurred in May and July 2025. Table 48 shows that Supplier M achieved an overall OTD rate of 99.58%, which is above target. The OTD trend is shown in Figure 20. Comparing the forecasting results, Supplier M maintained excellent delivery performance despite some variation in forecast accuracy. Table 49 suggests the remaining risk is mainly linked to short-term planning variability and temporary material shortages during under-forecasting. Based on these findings, it is recommended that Factory 2 maintain a stable forecast for Supplier M.

Table 49: Supplier M Forecasting and Delivery Performance (Factory 2, Italy)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 2 (Italy)	19.76%	16023.23	-0.75%	100.75%	99.58%	short-term planning variability, temporary material shortage risk

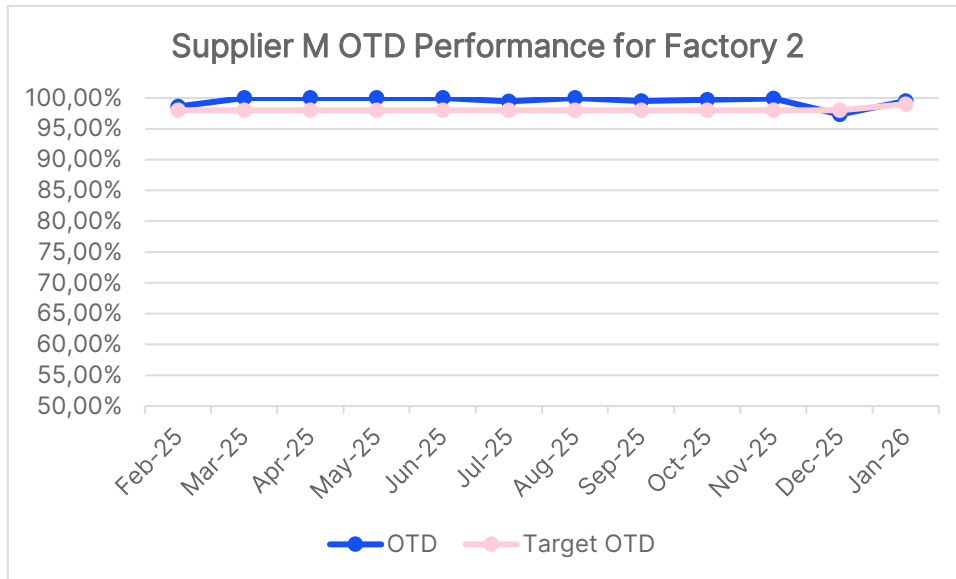


Figure 20: Supplier M OTD Performance for Factory 2

4.1.14 Supplier N Forecasting and OTD Performance

This part evaluates factory forecasting accuracy from both factory and supplier N delivery performance. Table 50 and 53 presents the MAPE calculations. Table 51 and 54 summarises supplier N OTD results. Table 52 and 55 provides an integrated explanation of both forecasting accuracy for both factory and supplier N delivery performance.

1. Supplier N Forecasting and OTD Performance for Factory 1

Table 50: MAPE Calculation for Supplier N (Factory 1, Finland)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $\frac{ A_t - F_t }{A_t}$
Nov-25	1202	324	-878	878	270.99%
Dec-25	1102	441	-661	661	149.89%
Jan-26	1006	388	-618	618	159.28%
Feb-26	880	472	-408	408	86.44%
Mar-26	1005	284	-721	721	253.87%
Apr-26	928	185	-743	743	401.62%
Total Average /	6123	2094	-4029	4029	MAPE = 220.35%

The forecast accuracy calculations are presented below for Factory 1:

Σ Forecasting Demand = 6123

Σ Actual Order Quantity = 2094

Forecast Bias = $(6123 - 2094) / 2094 \times 100 = +192.41\%$

Forecast Consumption = $2094 / 6123 \times 100 = 34.20\%$.

MAPE is the arithmetic average of the 6 monthly APE%, MAPE = 220.35%

RMSE = $\sqrt{(\sum(A_t - F_t)^2 / n)} = \sqrt{(2828083 / 6)} = 686.55$

Table 51: Supplier N OTD Performance (Factory 1, Finland)

Metric	Value
Σ Forecasting Demand	6123
Σ Actual Order Quantity	2094
Σ Delivered Quantity	2079
Overall OTD%	99.28%

Table 50 shows that factory 1 has a MAPE of 220.35%, an RMSE of 686.55, a forecast bias of +192.41%, and a forecast consumption of 34.20%. These metrics reveal poor forecasting performance and a strong tendency to over-forecast. Forecasted demand consistently larger than actual orders during the analysis period, indicating significant inefficiencies in the forecast planning process. Despite these issues, Table 51 shows Supplier N OTD at 99.28%, exceeding the company target, as shown in Figure 21. Delivery performance remained robust despite poor forecast accuracy from factory 1. Therefore, Table 51 identifies the main risks as planning inefficiency, unnecessary capacity reservation, and inventory issues, rather than delivery failure. Factory 1 should improve forecast planning for Supplier N.

Table 52: Supplier N Forecasting and Delivery Performance (Factory 1, Finland)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 1 (Finland)	220.35%	686.55	+192.41%	34.20%	99.28%	planning inefficiency

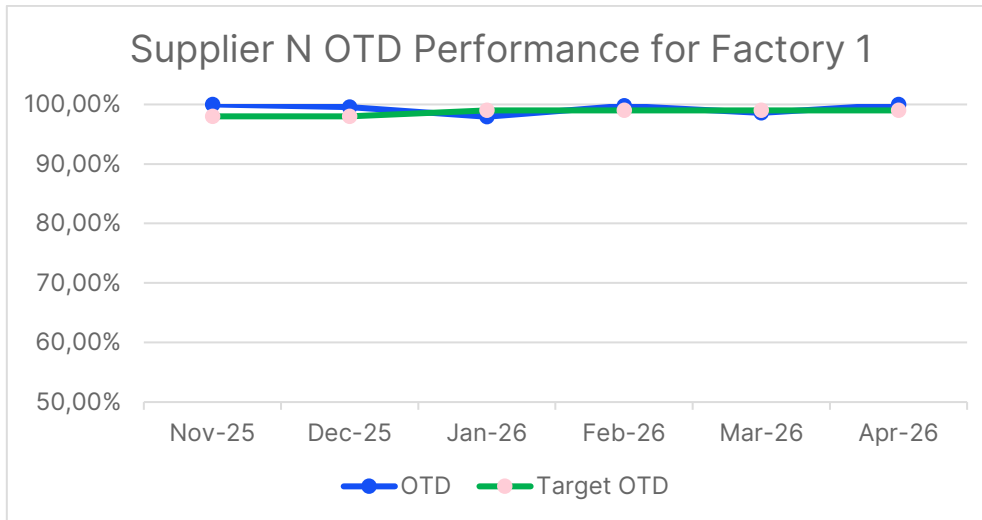


Figure 21: Supplier N OTD Performance for Factory 1

2. Supplier N Forecasting and OTD Performance for Factory 2 (Italy)

Table 53: MAPE Calculation for Supplier N (Factory 2, Italy)

Month	Forecasting Demand (F_t)	Actual Order (A_t)	Error ($A_t - F_t$)	Error	APE (%) = $ A_t - F_t / A_t$
Apr-25	56	11	-45	45	409.09%
May-25	53	14	-39	39	278.57%
Jun-25	55	40	-15	15	37.50%
Jul-25	73	60	-13	13	21.67%
Aug-25	65	54	-11	11	20,37%
Sep-25	38	142	104	104	73.24%
Oct-25	36	34	-2	2	5.88%
Nov-25	36	65	29	29	44.62%
Dec-25	36	40	4	4	10.00%
Jan-26	47	22	-25	25	113.64%
Feb-26	41	24	-17	17	70.83%
Mar-26	38	11	-27	27	245.45%
Total / Average	574	517	-57	331	MAPE = 110.91%

The forecast accuracy calculations are presented below for Factory 2:

Σ Forecasting Demand = 574

Σ Actual Order = 517

Forecast Bias = $(574 - 517) / 517 \times 100 = +11.03\%$

Forecast Consumption = $517 / 574 \times 100 = 90.07\%$.

MAPE is the arithmetic average of the 12 monthly APE%, MAPE = 110.91%

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(17381 / 12)} = 38.06$

Table 54: Supplier N OTD Performance (Factory 2, Italy)

Metric	Value
Σ Forecasting Demand	574
Σ Actual Order Quantity	517
Σ Delivered Quantity	517
Overall OTD%	100%

Table 53 shows that factory 2 has a MAPE of 110.91%, an RMSE of 38.06, a forecast bias of +11.03%, and forecast consumption of 90.07%. These metrics indicate weak forecasting performance and a consistent tendency to over-forecast. Forecasted demand exceeded actual orders for most of the period, suggesting unstable forecast planning. In contrast, Table 54 shows Supplier N achieved an overall OTD rate of 100%, exceeding the company target, as shown in Figure 22. Comparing the forecasting results reveals that delivery performance remained excellent despite poor forecast accuracy. Therefore, Table 55 identifies planning inefficiencies, unnecessary capacity allocation, and inventory risks rather than delivery failures. It is recommended that Factory 2 prioritise improving forecast planning for Supplier N.

Table 55: Supplier N Forecasting and OTD Performance (Factory 2, Italy)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 2 (Italy)	110.91%	3806	+11.03%	90.07%	100%	Inventory, planning inefficiency

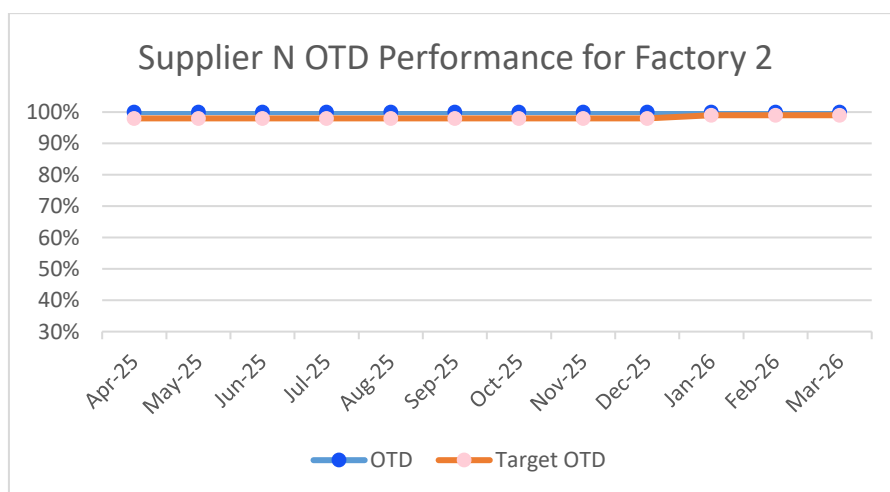


Figure 22: Supplier N OTD Performance for Factory 2

3. Comparative Analysis of Supplier N for Factory 1 and Factory 2

Forecasting performance from Factory 1 (Finland) and Factory 2 (Italy) shows poor accuracy, though OTD remained high from supplier N. Factory 1 had particularly poor metrics: MAPE of 220.35%, RMSE of 686.55, forecast bias of +192.41%, and forecast consumption of 34.20%. Factory 2 results were better but still insufficient, with a MAPE of 110.91%, an RMSE of 38.06, a forecast bias of +11.03%, and a forecast consumption of 90.07%. OTD rates stayed high at both factories: 99.28% at Factory 1 and 100% at Factory 2. Supplier N delivered reliably despite poor forecast accuracy. Overall, improvements to forecast planning are highly recommended at both factories.

4.1.15 Supplier O Forecasting and OTD Performance

This part evaluates factory forecasting accuracy and supplier O delivery performance. Table 56 presents the MAPE calculations. Table 57 summarises supplier M OTD results. Table 58 provides an integrated explanation of both forecasting accuracy and delivery performance.

Table 56: MAPE Calculation for Supplier O (Factory 5, Italy)

Month	Forecasting Demand (F)	Actual Order (A)	Error (A-F)	Error	APE (%) = $\frac{ A-F }{A}$
Feb-25	1148	1045	-103	103	9.86%
Mar-25	1032	1370	338	338	24.67%
Apr-25	1942	1827	-115	115	6.29%
May-25	1968	2208	240	240	10.87%
Jun-25	2494	4101	1607	1607	39.19%
Jul-25	3609	1870	-1739	1739	92.99%
Aug-25	1629	928	-701	701	75.54%
Sep-25	1097	1462	365	365	24.97%
Oct-25	1444	1306	-138	138	10.57%
Nov-25	1524	1513	-11	11	0.73%
Dec-25	800	974	174	174	17.86%
Jan-26	1898	2578	680	680	26.38%
Total Average	20585	21182	597	6211	MAPE = 28.33%

The forecast accuracy calculations are presented below for Factory 5:

Σ Forecasting Demand = 20585

Σ Actual Order = 21182

Forecast Bias = $(20585 - 21182) / 21182 \times 100 = -2,81\%$

Forecast Consumption = $21182 / 20585 \times 100 = 102.90\%$.

MAPE is the arithmetic average of the 12 monthly APE%, MAPE = 28.33%

RMSE = $\sqrt{(\Sigma(A_t - F_t)^2 / n)} = \sqrt{(6938715 / 12)} = 760.41$

Table 57: Supplier O OTD Performance (Factory 5, Italy)

Metric	Value
Σ Forecasting Demand	20585
Σ Actual Order Quantity	21182
Σ Delivered Quantity	17723
Overall OTD%	93.11%

Table 56 reports that factory 5 in Italy has an MAPE of 28.33%, an RMSE of 760.41, a forecast bias of -2.81% , and forecast consumption of 102.90%. These metrics indicate moderate forecast accuracy with a slight tendency to under-forecast. Table 57 shows that Supplier O achieved an OTD rate of 93.11%, below the company target, as shown in the OTD trend in Figure 23. Given these findings, Factory 5 must immediately implement targeted actions to improve forecast accuracy to support delivery performance from Supplier O. Under-forecasting causes material shortages, production disruptions, and urgent replenishments, which can harm operational continuity, as summarised in Table 58.

Table 58: Supplier O Forecasting and OTD Performance (Factory 5, Italy)

Production Site	MAPE (%)	RMSE	Forecast Bias (%)	Forecast Consumption	Overall OTD%	Risk
Factory 5 (Italy)	28.33%	760.41	-2.81%	102.90%	93.11%	Shortage, planning instability

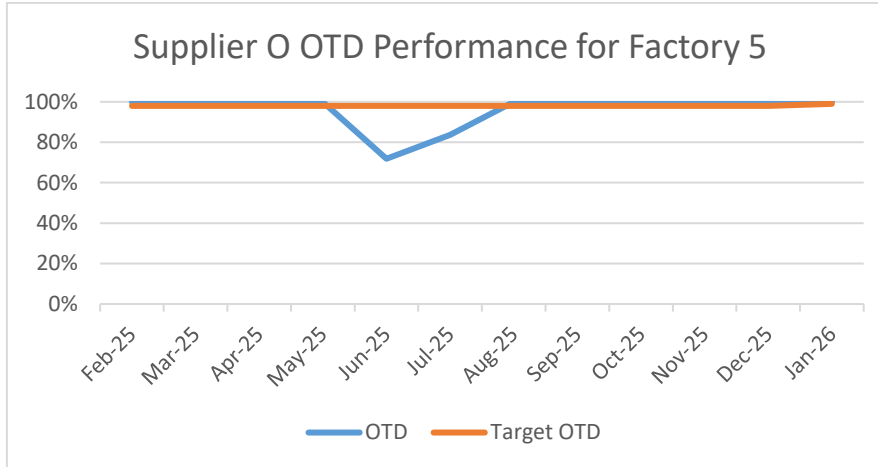


Figure 23: Supplier O OTD Performance for Factory 5

4.2 Qualitative Data Analysis Results

This qualitative analysis uses interview data from internal stakeholders within the Material Management team at the factory and European supply unit levels, along with input from Purchasing, Global Supply Planning, and selected external suppliers. After conducting the interview, the thematic analysis performed to decode the interview. The analysis identifies the forecast process, current gaps, practical limitations, and associated risk implementations of the existing forecasting process, and proposes recommendations with a swimlane flowchart (Yin, 2017; Syntetos et al., 2016).

Interviews revealed the main gaps in the forecasting process across manufacturing units in Italy, Finland, and the Czech Republic. Specifically, the key patterns are forecast period length, forecast breakdown logic, reliance on historical data, frequency of supplier reviews, and roles and responsibilities. Despite their differences, all units consistently use forecasting to manage material availability and prepare suppliers. Interviews clearly reveal that factories are not sharing the forecast with all their suppliers; it has been communicated only to selected suppliers based on business and volume. Also, forecast development and breakdown of the forecast planner heavily depend on Excel, manual translation of forecasts, experience, and rarely use formal key performance indicators (KPIs) for the forecast accuracy evaluation, which is clearly a gap to improve.

4.2.1 Forecasting Practices in Finnish manufacturing unit

Forecasting at the Finnish manufacturing unit is challenged due to the availability of planning data in detail. Demand is usually provided at a broad level, such as electrification volumes and full product levels, which require manual conversion to component and material levels. Then forecast planners combine historical consumption data by product, review inventory levels, safety stock targets, and open orders to complete project demand for configurable materials and safety components when high-level forecasts cover several material configurations. This process requires significant manual work and personnel experience, leading to forecast errors.

In Factory 3 in Finland, forecasts are updated monthly and are usually shared via Excel and email. Most forecasts cover three to six months, though some suppliers receive longer-term forecasts. Figure 24 shows that 81% of suppliers receive the forecast demand from Factory 3, which is under Supplier Quality Management scope, and on-time delivery data are measured. In comparison, the remaining 25% does not receive any forecast from factory 3 and needs to develop its own forecast based on historical consumption. In addition, there are no set rules for frozen periods on forecast updates, and forecast accuracy is not measured consistently.

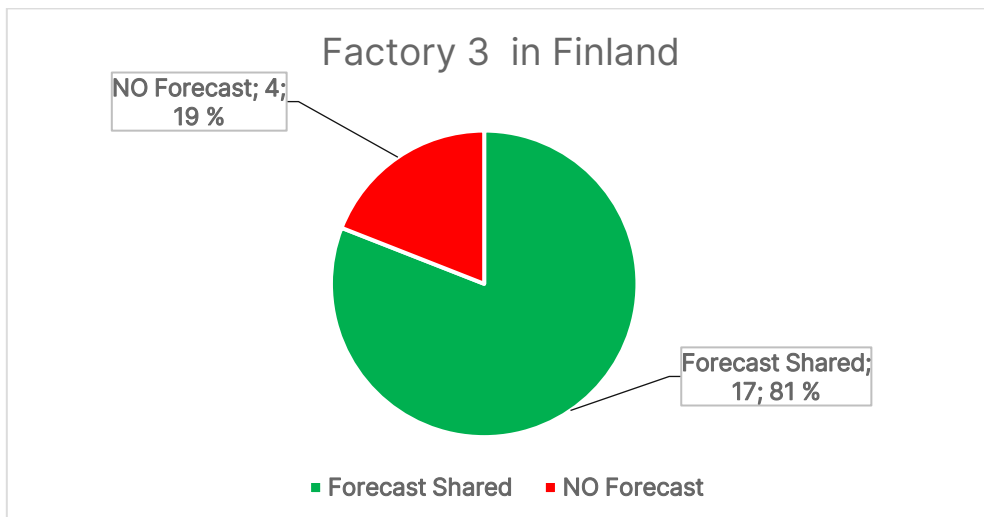


Figure 24: Finnish factory forecasted supplier Data

4.2.2 Forecasting Practices in Italian Manufacturing Unit

At the Italian manufacturing site, forecasting uses a make-to-order (MTO) approach. Because the products are customizable, the system cannot automatically generate component-level forecasts. Planners manually create forecasts for each component using overall demand data, historical usage, personal experience, and product knowledge. Supplier selection is based on lead time, consistency in prior deliveries, and compatibility with product customisation needs. The main challenge is that relying on individual expertise causes inconsistent forecasting outcomes and variability that hinder process standardisation.

Factory 2 uses a longer forecast period for selected suppliers to align with internal production planning, especially for electronics such as Printed Circuit Board Assembly (PCBA) and other critical materials with long lead times. Forecasts are updated monthly and are mostly shared with suppliers via Excel files. Figure 25 shows that Italian factory 2 aligns with the forecast at 85% with its suppliers, which Supplier Quality Management manages, and that their OTD has been measured and communicated by SQM. In contrast, the remaining 15% do not have a forecast from factory 2. In addition, about 55% of suppliers receive forecasts from Factory 5. In comparison, 35% do not have a forecast at all, and 10% deliver configurable materials and therefore do not have a forecast, as shown in Figure 26. The interview findings clearly illustrate that the lack of a standardised forecasting process and the absence of formal measurement of forecast accuracy mean that the current process supports only basic planning and limits systematic control.

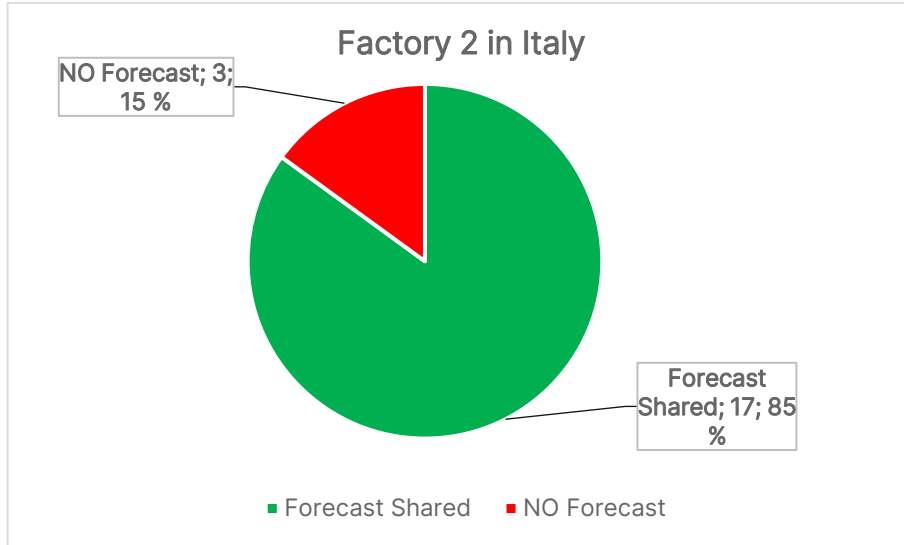


Figure 25: Italian Factory 2 forecasted supplier

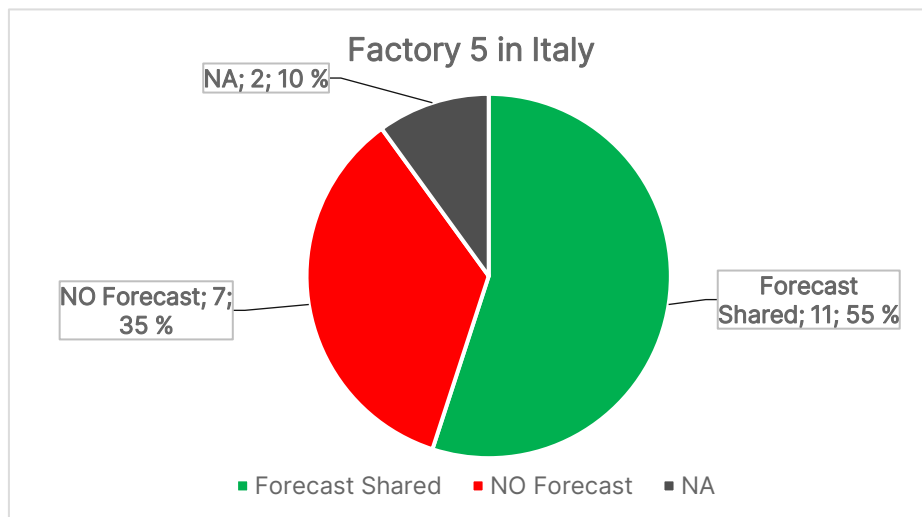


Figure 26: Italian factory 5 forecasted suppliers

4.2.3 Forecasting Practices in the Czech Republic Manufacturing Unit

The manufacturing unit in the Czech Republic uses a more structured forecasting approach than other units, but most tasks remain manual, as in other factories. Manual processes limit efficiency and accuracy, especially when forecasting stock materials in the mature phase of the product life cycle. Alternative processes manage configurable materials, phase-in or phase-out items, and items with change requests (CRs) through a

validation process. Forecasts rely on planned production volumes, historical consumption, and current production data. After creating forecasts, staff manually review and assign them to suppliers.

The main challenge in the Czech Republic unit is the lack of a unified formal process for preparing, reviewing, and updating forecasts, resulting in inconsistent forecasting practices. Forecasting responsibilities are spread across several teams. Forecasts are shared monthly, mainly through Excel files. Their accuracy is not systematically monitored with formal KPIs. Figure 27 shows Factory 4 shares the forecast with 61% of suppliers, managed by SQM and having OTD performance data, while 39% do not receive the forecast. The unit has a partially organised internal process but needs further standardisation and control to achieve consistent improvements in forecasting.

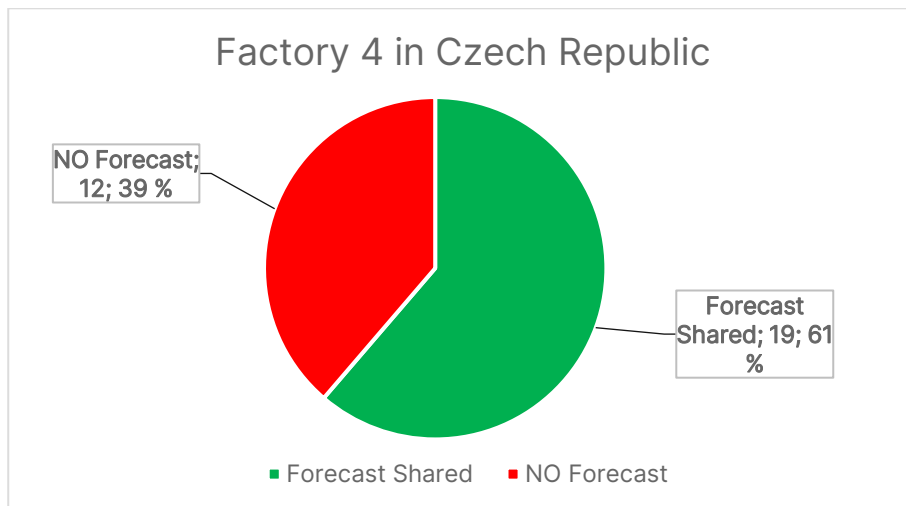


Figure 27: The Czech Republic factory 4 forecasted suppliers

4.2.4 Forecasting Practices at European Supply Unit Level

Within the European Supply Unit (ESU), the global supply planning team mainly handles forecasting, not the factory-level material management teams. Under the ESU scope, suppliers send products directly to the distribution centre rather than to individual factories. As a result, factory-level material management has limited visibility and involvement in forecast-based planning, reducing its ability to respond to local demand

changes. Forecasts are usually shared as Excel files for short-term and mid-term planning. According to interview information, about 75%-80% (exact number of suppliers unknown) of suppliers under the SQM scope receive the monthly forecast and have on-time delivery (OTD) data, while the rest do not, causing uneven supplier readiness. Coordination between ESU material management and suppliers is limited, causing delays in identifying supplier capacity issues. The current forecasting process does not adequately help suppliers prepare in advance, increasing the risk of supply problems.

4.2.5 Current Forecasting Process Flow

Figure 28 illustrates the existing forecasting process flow at the case company. The process starts with high-level demand inputs and continues through forecast translation, review, supplier communication, and execution. It involves only supply planning, the business unit, and material management. The current process relies on manual tasks, cross-functional coordination, and manual tools. These factors limit visibility, increase the risk of data inconsistencies, and slow decision-making compared to a standardised forecasting system.

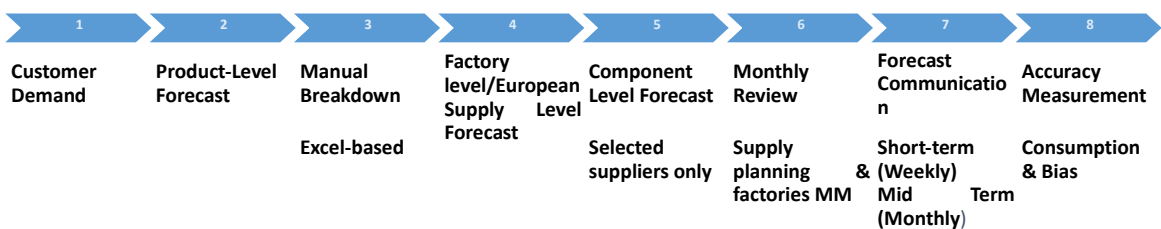


Figure 28: Current Forecasting Process Flow

4.3 Empirical Findings Analysis and Discussion

4.3.1 Interview Outcomes

The interview findings are based on semi-structured interviews with internal stakeholders from European manufacturing units in Finland, Italy, and the Czech Republic. The interviews explored the current forecasting process, process governance, data usage, supplier communication, and key challenges in the existing forecasting process. Participants included leaders and specialists from material management teams, supply planning representatives, purchasing stakeholders, and supplier quality management. All respondents were selected for their direct involvement in forecasting process activities and supplier coordination. As a result, the interview data offers a cross-functional and cross-unit view of current forecasting process practices. The interview outcomes are below:

1. Forecasting Practices at Manufacturing Unit in Italy

Interviews at the Italian manufacturing unit indicate that the main forecasting challenge relates to manual processes and is heavily influenced by the make-to-order (MTO) structure of the safety component product platform. Because customer orders are highly configurable and lack a predefined bill of materials (BOM) at order intake, forecasts cannot be system-generated, and manual interpretation of aggregated demand is required. In addition, these findings show that global demand forecasts are only available at a high level and are manually converted into component-level forecasts using historical data, planner expertise, and detailed product knowledge. Interviewees stated that a manual approach is necessary due to the complex and variable product configurations. Furthermore, the forecast horizon exceeds internal lead times, particularly for electronic components, where suppliers may require up to twelve months of advance visibility.

The main challenges identified in interviews are the lack of a standardized forecasting process, inconsistent approaches to managing forecasts, and ineffective supplier collaboration. Currently, forecast updates are shared monthly with selected suppliers via Excel. However, binding periods and approval methods vary across material groups, such

as electronic board and drive components. There is no clear standard for a forecast-freeze period. The findings also show that forecast accuracy is not systematically measured, and no formal KPIs are used to assess forecast performance at the component or supplier level. Supplier OTD is measured by supplier quality management, but only for selected suppliers.

Furthermore, the interview findings indicate that supplier capability is not assessed, and only strategic electronics suppliers participate in regular review meetings. As a result, these suppliers often respond only after purchase orders are issued, limiting the benefits of proactive long-term forecasting. To resolve these issues, standardize forecasting processes across all material groups, consistently monitor forecast accuracy and KPIs at both the component and supplier levels, and schedule structured capacity supplier reviews meetings for each supplier to strengthen collaborative forecasting and ensure continuous supplier engagement.

2. Forecasting Practices at Manufacturing Unit in Finland

Interview findings from the Finnish manufacturing unit indicate that the main obstacles to reliable forecasting are limited data granularity and ongoing organizational changes in Materials Management. Instead of component-specific forecasts, demand information is provided as high-level planning input, such as electrification volumes. As a result, the Materials Management team must manually convert this input into component-level forecasts, relying on historical consumption, personal experience, product knowledge, stock levels, safety stock, and open orders. The interviews reveal that this translation process creates significant uncertainty, since a single high-level variant can cover several material combinations. Thus, while overall volume forecasts may be broadly accurate, component-level forecasts are less reliable. Consequently, forecast accuracy KPIs are not used, as interviewees stated that these measures offer limited practical value in the current process.

The study findings show that current forecast horizons typically range from 3 to 6 months, depending on material and supplier agreements, while some suppliers or materials use longer horizons. Forecasts are updated monthly and communicated manually, mainly through Excel files sent by email. Furthermore, the absence of a common policy for frozen or forecast update periods leads to variation in forecasting practices across supplier relationships.

Based on the above findings, Standardize translating high-level forecasts to component-level forecasts and, where feasible, implement forecast accuracy KPIs. Establish a policy governing forecast changes and frozen periods to unify practices across suppliers. Extend alternative forecasting pilots to additional suppliers, with scheduled evaluations of effectiveness. Automate forecast communications to minimize manual intervention.

3. Forecasting Practices at Manufacturing Unit in Czech Republic

Interview findings from the manufacturing unit in the Czech Republic show that internal forecasting processes are more structured than in other units, but the approach remains manual, like in other factories. The manual process involves planners collecting planned production volumes, historical consumption data, and actual production figures from spreadsheets and internal databases. Planners manually consolidate this data, typically using the previous three months as the main reference point. The factory creates a rolling four-month forecast with this information, which is reviewed and adjusted by planners before being allocated to suppliers based on quota arrangements and replenishment parameters. Each planner is responsible for maintaining forecasts for their assigned materials and suppliers.

Moreover, Forecasts are shared monthly with suppliers via Excel files, but there is no centralized approval process or formal guidelines for preparing, reviewing, or adjusting forecasts. Forecast accuracy is also not systematically measured using KPIs. The main challenge, according to interviewees, arises during ramp-up and ramp-down phases, when historical data is less reliable. These ramp-up and ramp-down profiles are not fully

visible to the material management and supply planning team, revealing a clear process gap.

The interviews indicate that initial harmonization efforts are underway. For example, the unit encourages aligned forecasting practices for certain material categories, like metal sheets, through benchmarking and factory collaboration. Interviewees recommend systematic monitoring of forecast accuracy using KPIs and regular review sessions across units. Cross-functional alignment is also needed on ramp-up and ramp-down profiles to improve visibility for the material management team. These actions can promote standardization and enhance forecasting effectiveness across manufacturing units.

4. Forecasting Practices with European Supply level Suppliers

Interviews indicate that ESU-level supplier forecasting is mainly managed by the global supply planning team rather than by factory unit material management. Forecasts are typically communicated to suppliers by manually compiling data into Excel spreadsheets and sending them via email for both short- and mid-term planning. However, coordination remains limited because regular cross-functional meetings are rare. Material management primarily aims to match forecasted demand with production needs and to react when deviations occur. The absence of regular alignment meetings and formal KPIs hinders early assessment of supplier readiness. When forecast information are unclear, suppliers often rely on historical demand, which increases capacity risk. The findings also show supplier capacity issues are often identified only after delivery problems. For this reason, interviews highlighted the need for better governance, clearer forecast communication, and measurable KPIs, such as forecast accuracy. These improvements should increase coordination and enable proactive forecasting.

Major interview findings are below:

- 1) **Manual and Fragmented Process:** The current forecasting process is manual and split between tools. Excel is used to create and update forecasts; Power BI and Qlik Sense

are used for reporting. This setup relies on planners, increases error risk, and makes tracking changes difficult.

- 2) **Non-Standard Forecast Breakdown:** Forecasting starts at the full product level and is then broken down to component and material levels, using historical demand, manual updates, and planner input. This leads to inconsistent logic across time and units.
- 3) **Absence of a Formal Freeze Window:** Currently, no forecast has been established for the freeze period, and existing forecasts changes monthly, even in the short term. This variability reduces predictability and increases operational pressure on factories and suppliers, making complicating resources allocation, workforces management, and meet delivery timelines.
- 4) **Inconsistent Forecast Sharing:** Forecasts are shared with only selected suppliers, typically on a case-by-case basis with Purchasing. However, all suppliers are not receiving the forecasts, reviews are limited, and supplier feedback is not consistently included. As a result, information sharing and collaborative planning are limited
- 5) **Limited Forecast KPIs:** Forecast accuracy is assessed by monitoring consumption forecasts for only a small group of suppliers. Forecast bias is tracked for even fewer suppliers. Current measurements are mainly retrospective. No one reviews changes between forecast versions or trends in supplier-specific accuracy. These KPIs only support reporting and do not drive improvements. Additionally, the limitations in KPI effectiveness are mirrored by process governance challenges.
- 6) **Limited Process Governance** Monthly factory review meetings occur, but forecasting governance is weak. While Supply Planning oversees demand forecasting, Purchasing manages supplier relations, factories focus on production execution, and material management handles inventory, these roles are generally understood but are not formally defined or standardized.

4.3.2 Forecasting Accuracy and supplier On-Time Delivery Performance

The empirical findings from the quantitative analysis for Suppliers A to O are based on the analysis of forecasting accuracy metrics, including MAPE, RMSE, forecast bias, and forecast consumption, across selected factories. In addition, evaluating supplier On-

Time Delivery (OTD) performance for the selected factories provides further insights. Together, these analyses allow this study to directly assess how forecasting deviations affect delivery performance, planning stability, inventory levels, and operational risk at the supplier level.

Supplier A shows poor forecasting accuracy from both Factory 1 and Factory 2, and supplier on-time delivery is below the target at both sites. While Factory 2 demonstrated slightly better forecasting than Factory 1, its OTD is still lower. In both factories, forecasted demand exceeded actual orders, indicating an over-forecasting trend. This over-forecasting can lead to excess inventory, inefficient supply planning, supplier capacity issues, and less effective resource planning. Therefore, Supplier A needs accurate forecasting from both factories to improve delivery performance, while Factory 2 requires more urgent attention due to its very low OTD.

Supplier B showed different patterns in Factory 1 and Factory 2. In Factory 1, forecasting accuracy is acceptable, but OTD remains below the target. Actual demand exceeded forecasts, suggesting under-forecasting caused shortages and urgent replenishments. In Factory 2, forecasts are accurate, but OTD is still poor, indicating issues with delivery execution. These differences indicate that Supplier B must improve its delivery and supply chain planning. This case proves that good forecasting alone does not ensure good delivery performance.

Supplier C indicates a clear difference between Factory 1 and Factory 2. In Factory 1, forecasting accuracy is acceptable, but supplier C delivery performance remains poor. Actual demand exceeded forecast demand, indicating under-forecasting and resulting in material availability issues, and urgent replenishment is needed, which might have a small impact on delivery. In Factory 2, forecasting accuracy is extremely poor, and OTD is also very poor from supplier C. Forecast demand is substantially higher than actual demand, indicating strong over-forecasting. This reflects a significant mismatch between planning and actual demand. Such a condition may have contributed to planning inefficiency, excess inventory, and unstable delivery performance. Overall, Factory 2 needs to

improve its forecast accuracy, on the other hand, supplier C needs to improve the delivery performance.

Supplier D received poor forecasting performance from both factories, while delivery performance was achieving the target level. In Factory 1, actual demand exceeded forecast demand in every month, indicating a clear pattern of under-forecasting. In Factory 2, forecasting performance is slightly better, but it is still weak forecasting. Despite these forecasting limitations, both factories received good OTD. However, this weak forecasting continues to pose significant risks for future planning, including material shortages and urgent replenishment. To address these persistent issues, both factories must implement robust, proactive forecasting processes to reduce errors and ensure consistently stable OTD.

Supplier E in Factory 3 shows moderate forecasting performance, but supplier delivery performance remained below the target. Forecast demand is slightly higher than actual orders, indicating over-forecasting, and several months indicate clear differences between forecast and actual demand. This suggests that forecasts are not sufficiently stable to support reliable planning. At the same time, weak supplier OTD also indicates challenges in delivery execution. Overall, Supplier E requires strong forecasting accuracy to improve delivery performance and reduce inefficiency and unreliability. On the other hand, suppliers need to investigate the root cause and develop a corrective action plan (CAPA) to improve their delivery performance.

Supplier F in Factory 3 achieved acceptable forecasting, but OTD remained below target. Forecasts slightly exceeded actual demand, indicating mild over-forecasting. Although overall forecasts generally matched demand, there were clear deviations in some months. Forecasting accuracy is acceptable but fluctuates monthly. The low OTD shows that delivery execution is weaker than forecast accuracy. Supplier F needs more stable forecasting to support OTD, and suppliers need to improve delivery performance by creating an action plan.

Supplier G in Factory 1 demonstrates poor forecasting accuracy and delivery performance below target. Forecast demand is substantially lower than actual demand, indicating significant under-forecasting. Actual demand is more than double the forecast, revealing that forecast planning does not align with actual demand. Supplier on-time delivery is below target, indicating delivery performance cannot meet expectations due to very poor forecasting accuracy. This situation creates significant operational risk, including material shortages, urgent replenishment, additional air-shipping costs, and production disruptions. Overall, Factory 1 must improve forecasting performance to ensure better supplier G delivery management.

Supplier H reports weak forecasting performance from factory 2, which has resulted in poor delivery outcomes. Although total forecasts and actual orders appear aligned, there are significant variances from month to month. This indicates that overall numbers conceal considerable instability between months. Supplier H's on-time delivery remains well below target, mainly due to inaccurate forecasts from factory 2. To enhance delivery performance, Factory 2 should focus on producing and sharing more accurate forecasts with Supplier H.

Supplier I demonstrated weak forecasting performance from factory 2, while delivery performance remained consistently high. Although the aggregate forecast closely approximated actual orders, significant deviations occurred in several months, indicating instability in the forecasting process. In contrast, Supplier I on-time delivery (OTD) consistently met the target, suggesting that strong delivery performance compensated for forecasting deficiencies. Factory 2 should focus on improving forecasting stability for Supplier I, and Supplier I should continue maintaining robust delivery performance.

Supplier J in factory 4 demonstrated acceptable forecasting performance and strong delivery performance. Forecasted demand closely matched actual orders, though some months showed larger deviations. These results indicate that forecasting performance is generally reliable but not fully stable. Supplier J On-time delivery consistently exceeded the target, reflecting robust delivery performance. It is recommended that Supplier J

maintain its high delivery standards, and Factory 4 should focus on improving forecast consistency.

Supplier K at factory 4 demonstrated strong forecasting accuracy and exceptional delivery performance. In most months, forecasted demand closely matched actual orders, with forecasting remaining stable throughout the period. Furthermore, Supplier K consistently exceeded the on-time delivery (OTD) target, reflecting robust delivery capabilities. Only a few months showed significant forecast deviations. It is recommended that Factory 4 maintain its current forecasting practices for Supplier K, and that Supplier K continue to sustain its high delivery performance.

Supplier L at factory 4 indicates weak forecasting and delivery performance. Although the total forecasted and actual order volumes were similar, the monthly forecast pattern was highly unstable, with several months exhibiting significant deviations. As a result, comparable total volumes do not necessarily indicate high forecasting quality. This unstable forecasting also contributed to supplier L on-time delivery consistently falling below the target. In summary, factory 4 requires accurate forecasting to improve supplier L delivery performance reliability.

Supplier M at Factory 2 shows strong forecasting accuracy and reliable delivery performance. Forecasted demand generally matches actual orders, with only occasional larger monthly deviations, indicating high accuracy but some need for improved stability. On-time delivery exceeded the target, confirming strong performance. Supplier M should maintain its delivery standards, while Factory 2 should continue its consistent forecasting.

Supplier N shows very weak forecasting performance from both Factory 1 and Factory 2, while delivery performance is very good. From Factory 1, forecast demand is much higher than actual orders, indicating severe over-forecasting. From Factory 2, forecasting performance was also very poor, with large monthly deviations, although OTD reached 100%. This suggests that the main weakness is forecasting accuracy rather than the supplier N delivery execution. However, poor forecasting may still lead to planning ineffi-

ciencies, excess inventory, and unnecessary capacity utilization. Overall, Supplier N requires good forecasting accuracy from both factories while maintaining its strong delivery performance.

Supplier O in Factory 5 indicates moderate forecasting accuracy and failed to meet delivery targets. Forecasted demand was usually below actual orders, with several months showing large gaps. This pattern shows unstable forecasting, meaning actual orders have been placed without a forecast, or orders have been over-forecast. The poor forecasting accuracy from factory 5 impacts the supplier O delivery performance, which is below target. Supplier O needs stable forecasting accuracy from factory 5 to improve delivery performance, reduce shortage risks, support inventory management, and urgent material replenishments.

Overall, the findings indicate that forecasting performance and on-time delivery (OTD) are not consistently correlated across suppliers and factories. Some suppliers achieved strong delivery outcomes despite weak forecasting accuracy, while others maintained acceptable forecasting accuracy but failed to meet OTD targets. These results indicate that forecasting accuracy alone does not fully explain delivery performance. Supplier delivery performance is also influenced by factors such as supplier capabilities, geopolitical issues, geographic location, and culture. Furthermore, the analysis shows that both under-forecasting and over-forecasting introduce operational risks. Under-forecasting can lead to material shortages and require urgent replenishment, whereas over-forecasting may result in excess inventory, inefficient resource allocation, and other inefficient capacity utilization. Therefore, robust supplier performance depends on both accurate forecasting and reliable execution of deliveries.

4.3.3 Impact of Forecasting Accuracy on On-time Delivery Performance

Table 58 compares forecasting accuracy and on-time delivery performance to show if forecasting accuracy affects delivery performance.

Table 59: Impact of forecasting accuracy on on-time delivery performance

Supplier	Factory Forecasting Accuracy	OTD Performance	Did Forecasting accuracy Impact OTD?
Supplier A	Factory 1: Poor. Factory 2: Poor but better than Factory 1	Below target in both factories, Poor in Factory 2	Yes. Weak forecast accuracy leads to the low OTD, while Factory 2 has other issues as well.
Supplier B	Factory 1: Acceptable. Factory 2: Good level	Below target in Factory 1 and poor in Factory 2	Partly. In Factory 1, under-forecasting leads to weak OTD, While Factory 2 forecasting does not appear to have been the main cause of poor OTD.
Supplier C	Factory 1: Acceptable. Factory 2: Extremely poor	Both factories have poor OTD	Yes. Forecasting deficiencies affected OTD in both factories, particularly Factory 2, Over-forecasting leads poor OTD.
Supplier D	Factory 1: weak; Factory 2: weak but slightly better	Very good in both factories	No immediate impact on OTD. Good delivery execution appears to have compensated for weak forecasting.
Supplier E	Factory 3: moderate	Below target	Yes. Forecasting instability impact to poor OTD.
Supplier F	Factory 3: Acceptable	Below target	No. Acceptable forecasting accuracy, so poor OTD seems to be more related to other issues.
Supplier G	Factory 1: very Poor	Poor	Yes. Severe under-forecasting directly impacts poor OTD.
Supplier H	Factory 2: weak	Very poor	Yes. Forecasting instability impact on very poor OTD.
Supplier I	Factory 2: weak	Very strong	No. Though future planning risk
Supplier J	Factory 4: Acceptable	Very good	No.
Supplier K	Factory 4: Good	Excellent	No. Good forecast supported strong OTD.
Supplier L	Factory 4: weak with large deviations	Poor	Yes. Forecasting instability leads to poor OTD.
Supplier M	Factory 2: Acceptable	Excellent	No. Good forecast supported excellent OTD.
Supplier N	Very poor in both factories.	Very good in both factories	No. However, poor forecasting created planning inefficiency and operational risk.
Supplier O	Factory 5: Moderate with large monthly deviations	Below target	Yes. Forecasting variation and under-forecasting leads to low OTD and shortage risk.

4.3.4 Comparative Analysis of Supplier Performance Based on Forecast Accuracy

The comparison identifies two distinct groups of suppliers regarding forecast and on-time delivery (OTD) performance. The first group, including Suppliers G, O, H, L, A, and C, demonstrated that poor or unstable forecasting is associated with weaker supplier delivery performance. For example, Supplier G has under-forecasted for the case company and achieved poor OTD, suggesting that a lack of forecast visibility leads to material shortages and delivery delays. Similarly, Supplier O faced forecast variation and under-forecasting linked to shortage risk and below-target OTD. Suppliers H and L indicate weak forecasting and large monthly deviations, which coincided with poor delivery performance and indicated that unstable demand signals reduced planning reliability. Suppliers A and C further support this pattern, as weak forecasting is associated with weak OTD across factories. Meanwhile, the second group, including Suppliers D, I, and N, maintained strong OTD despite weak forecasting, which suggests that effective operational execution can partly offset forecasting deficiencies, at least in the short term. Overall, the findings indicate that poor or unstable forecasting can negatively affect OTD by reducing demand visibility, leading to material shortages, affecting inventory management, capacity, and delivery planning. These findings address the research question by showing that forecasting performance influenced supplier OTD performance in several cases. However, other factors influence delivery performance across suppliers, including operational execution capability, geopolitical issues, geographical location, transportation, and culture.

5 Conclusion and Recommendations

5.1 Conclusion

The study concludes by summarizing the key findings, answering the research questions, and proposing a recommendation. It also presents a swimlane process flowchart and outlines the research academic outcomes. The study combines qualitative and quantitative evidence to show that current forecasting practices impact supplier on-time delivery performance in the case company. This is based on an investigation of the forecasting process in selected European manufacturing units and an analysis of the relationship between forecasting accuracy and supplier OTD. A mixed-method case study approach is used, joining qualitative findings on forecasting practices with quantitative analysis using four KPI metrics: MAPE, RMSE, Forecast Bias, and Forecast Consumption.

The research findings show that demand forecasting is crucial for maintaining smooth production in the case company. However, the current forecasting process is not standardized across selected factories and global supply planning levels. Key gaps include variations in forecast horizon, frozen period, breakdown or conversion logic, ownership, review routines, and supplier communication. Additionally, the process relies on manual work, individual experience, and Excel-based methods, affecting forecast consistency, transparency, and cross-functional alignment. Quantitative analysis also indicates that poor forecasting accuracy creates operational challenges, unstable planning, and inventory management issues. Supplier OTD performance is further influenced by other factors such as delivery capability, geopolitical issues, supplier location, cultural issues, and transportation problems.

Overall, the research finds that improving supplier on-time delivery performance requires more than just better forecast accuracy. It also shows that a standard forecasting process, strong cross-functional alignment, clear governance, consistent KPI follow-up, and reliable supplier communication are crucial for achieving sustainable improvement. This study identifies gaps in the current forecasting process and highlights the need for

standardization, providing a realistic foundation for future improvements in supplier on-time delivery performance.

1. RQ1: What forecasting practices are currently used across the selected manufacturing units, and how are these practices misaligned?

The study finds that all European manufacturing units use forecasting for only selected suppliers, and the process is not yet fully standardized. Each manufacturing unit in Finland, Italy, and the Czech Republic uses its own forecast approach. Demand forecasting supports material planning, production scheduling, and supplier preparations, but practices vary across factories in several areas, including forecast horizons, frozen periods, forecast conversion logic, ownership, review routines, and supplier communication.

The qualitative data analysis indicates that the current forecasting process mainly relies on manual processes in this case. High-level demand signals are converted into component-level forecasts using Excel-based calculations, historical consumption data, personnel experience, and local assumptions patterns. This forecast conversion step shows clear uncertainty and potential errors in the current forecasting process. Furthermore, the demand forecast has been shared with only selective suppliers based on the business case and volume. Statistics show that around 60–70% of suppliers under the SQM rush report list receive forecast information and have an OTD performance record. In addition, supplier forecast follow-up communication for the forecast reliability is selective and not consistently harmonized across manufacturing units.

Furthermore, the study findings indicate that the forecast accuracy measurement KPI is limited for the company. Although the forecast consumption and forecast bias metrics are used in a few specific cases, there is no standard alignment KPI for the material management and supply planning team to measure forecast accuracy across all factories. Additionally, forecast governance is not standardized, as roles, responsibilities, and the escalation process are not fully aligned across functions.

In response to RQ1, it is evident that forecasting practices are used across all factories only for specific suppliers, but the processes are not fully standardized. The current forecasting process is manual, where high-level demand signals are converted into component-level forecasts using Excel-based calculations, historical consumption data, personnel experience, and local assumptions and patterns. Moreover, clear cross-functional misalignment appears in several areas, including forecast horizons, frozen periods, forecast conversion logic, ownership, review routines, and supplier communication.

2. RQ2: How does forecasting performance relate to supplier On-Time Delivery performance in the selected manufacturing units?

The quantitative results indicate that forecasting accuracy significantly affects supplier on-time delivery performance. However, other factors also influence the supplier's delivery performance. Many supplier cases demonstrate poor forecasting accuracy, which correlates with poor OTD. Under-forecasting leads to material shortages, urgent replenishment needs, and increased pressure on effective production planning. In contrast, over-forecasting raises the risk of excess inventory, unstable planning, and misallocated capacity. In both cases, poor forecast accuracy undermines planning stability and on-time delivery performance.

The findings illustrate that good forecasting accuracy alone does not guarantee achieving the targeted on-time delivery performance. For example, some suppliers demonstrate acceptable or good forecast accuracy, but their delivery performance remains below target. This suggests that supplier delivery performance is influenced by additional factors, such as supplier execution capability, geopolitical issues, geographic location, culture, material lead-time alignment, and shop-floor operational discipline. Conversely, some suppliers achieve targeted OTD performance even with poor forecasting. This indicates that strong capabilities, such as sufficient safety stock management from global or large suppliers, can partly compensate for weaknesses in forecasting. In contrast, small and medium suppliers, lacking robust safety stock management (which falls outside the agreement), are unable to cover under-forecasted orders.

In answer to RQ2, forecasting performance is closely connected to supplier on-time delivery (OTD) performance, though the relationship is not entirely direct. Poor forecasting can result in weak supplier delivery performance due to insufficient materials, poor inventory management, unstable planning, production scheduling issues, and urgent replenishments. Additionally, supplier OTD depends on other factors such as supplier implementation capability, geopolitical issues, geographic location, culture, lead-time agreements, shop-floor operational discipline, and operational readiness.

3. RQ3: How can a standardized forecasting process improve cross-functional alignment, and supplier On-Time Delivery performance?

The findings show that the standard forecasting process can influence forecast performance and support good supplier delivery performance. A standardized forecasting process establishes one common forecasting approach among all factories and relevant stakeholders. It also defines clear roles and responsibilities for preparing, reviewing, approving, and communicating forecasts to the supplier. Misalignments can occur if roles are unclear or if communication breaks down, potentially leading to inconsistent or inaccurate forecasts. Moreover, forecast process standardization supports better comparability across units by using common KPIs and review guidelines, while facilitating more stable and consistent communication with suppliers

The qualitative findings illustrate that the current forecasting process across selected factories results in reduced transparency and poor cross-functional alignment. Specifically, variability in forecast assumptions, horizons, frozen periods, and review routines among stakeholders from different factories prevents the case company from developing a unified forecasting perspective. Consequently, supplier management becomes complicated, as the case company is limited in its ability to learn from forecasting errors. Therefore, implementing a standardized forecasting process can strengthen alignment between global supply planning, purchasing, material management, engineering, and supplier quality management. Furthermore, it would encourage more structured review routines for forecast accuracy and facilitate better escalation of forecast-related risks.

In response to RQ3, implementing a standardized forecasting process can enhance cross-functional alignment, improve supply planning consistency, and enhance supplier on-time delivery performance by developing a simple, common forecasting logic across all manufacturing units. This approach can simplify roles and responsibilities, align review routines, develop common KPIs, and improve communication with suppliers.

5.2 Literature Reflection

The findings of this thesis closely match the literature reviewed. For RQ1 and RQ3, the literature shows that forecasting is not only the statistical task, but also a cross-functional planning capability. Alignment in forecasting depends on process design, governance, and organizational structure that enable supplier readiness and delivery performance. The study therefore observes clear differences in forecasting practices among the selected manufacturing units, which leads to misalignment. Standardizing the forecasting process can improve clarity, coordination, ownership, and the quality of resolution across different functions (Oliva & Watson, 2009; Gilliland et al., 2016; Vandeput, 2023).

Regarding RQ2, the study supports existing literature on measuring delivery performance through forecast accuracy KPIs. Using metrics such as MAPE, RMSE, forecast bias, and forecast consumption matches the study recommendation for a balanced set of KPIs to evaluate forecast errors, direction, and realization. Weak forecasting raises the risk of material shortages, inventory management problems, planning inefficiency, and issues with supplier capability readiness. However, the study also shows that forecasting accuracy alone does not ensure good supplier delivery performance, since this is also affected by supplier capability, geopolitical factors, geographic location, culture, and transportation. This finding aligns with the literature, which notes that although the forecast process supports supply planning, delivery performance depends on additional factors (Gilliland et al., 2015; Vandeput, 2023).

This study addresses all three research questions and supports existing literature on the relationship between forecasting and delivery performance. Prior research indicates that

weak forecasting can result in shortages, excess inventory, planning instability, and impact delivery performance; findings from this thesis are consistent with these conclusions. However, the results also reveal that forecast accuracy alone does not ensure improved supplier delivery performance. Collectively, the study makes a contribution by providing clear evidence that current practices in forecasting, governance, and supplier communication influence supplier on-time delivery performance across different manufacturing units (Gilliland et al., 2015; Oliva & Watson, 2011; Vandeput, 2023)

5.3 Managerial Recommendations

Based on the study outcomes, this section proposes several managerial recommendations to improve current forecasting practices and support supplier On-Time Delivery performance at the case company.

First, the company should develop a standard forecasting process for the chosen European manufacturing sites by first defining common planning steps. This process must also include clearly specified forecast horizons, update frequencies, frozen periods, review routines, and regular supplier communication. Clarifying and aligning these elements will minimize local process differences and ensure consistent planning across sites.

Second, the roles and responsibilities of the planning, purchasing, materials management, and supply chain teams should be clearly defined. Defining clear responsibilities will improve accountability and reduce mistakes in preparing forecasts, conducting reviews, and communicating with suppliers.

Third, the case company should standardize the forecast conversion logic from high-level demand to component-level forecasts. Since this step is handled manually in Excel using planners experience and historical consumption patterns, establishing standard rules and assumptions will help reduce variation between supply planners and factories, ensuring a more reliable demand forecast.

Fourth, the case company should implement a balanced forecast measurement using a metric KPI framework across all relevant factory units. To ensure ongoing effectiveness,

the company should regularly review KPI metrics such as MAPE, Forecast Bias, and Forecast Consumption. Upon identifying forecast accuracy issues, the team should analyze the root cause and develop a corrective action plan.

Fifth, the case company should organize monthly cross-functional team meetings that include supply planning, purchasing, material management, engineering, and supplier quality management. A structured monthly review will help relevant stakeholders align assumptions, discuss major issues and risks, and agree on improvement actions. This approach will improve coordination and strengthen managed forecasting.

Sixth, the case company should establish consistent communication with suppliers regarding the forecast. It is important to clearly define the rules for forecast visibility and alignment. This includes discussing and agreeing on long-lead materials. Maintaining a stable and transparent forecast communication and review process will help suppliers improve their capacity, capability, and supply chain planning.

Seventh, the case company should establish clear forecast frozen periods as a standard process. Currently, too many short-notice forecast changes occur, which impacts delivery performance because suppliers have limited time to prepare. By setting a standard frozen period, forecasts would become more stable. This stability would improve delivery performance by reducing last-minute disruptions across internal functions and suppliers.

Eighth, the case company should gradually reduce its reliance on manual tools, planner experience, and Excel-based forecasting. The company should begin developing automation platforms to manage forecast data and automate high-level demand breakdown logic to the component level. These steps will help reduce errors, minimize manual effort, and accelerate process improvement.

To summarize, these recommendations align with the findings from the literature review. Previous research shows that improving forecasting processes depends not only on standard models but also on structured processes, clearer governance and ownership, KPI-based learning, and cross-functional alignment. Therefore, both the study findings and the literature review support these recommendations.

5.4 Proposed Standard Forecasting Process

The proposed standard forecasting process improves cross-functional alignment, clarifies stakeholder roles, and ensures consistent supplier communication. By implementing eight detailed steps, this process enables more accurate demand forecasting, reduces supply disruptions, and increases on-time supplier deliveries. Clear mapping of activities, decision points, and KPI monitoring establishes accountability, enhancing overall supply chain performance. Furthermore, this study proposes three KPIs for evaluating forecast accuracy in the case company: MAPE, Forecast Bias, and Forecast Consumption.

Table 60: Proposed standard forecasting process

Process step	Global Supply Planning	Material Management	Purchasing	Engineering	Suppliers
1. Consolidate monthly demand signal	Establish baseline demand in SAP.	Develop forecast calendar constraints, and baseline	Develop constraints including LT, Quotations and binding rules.	Change Update: New releases, EOL, and CR implementation timelines	Supply constraints: Capacity and material availability
2. Build product level forecast baseline	Develop forecast baseline for statistical and planner review	Review peaks season and local impact			Ensure Demand feasibility
3. Forecast translation using BOM	Develop SAP-based conversion logic	Translate component level forecast using SAP logic	Review Quotations	Update BOM and alternatives material	Ensure planning parameters like LT, MOQ, and batch size.
4. Change Validation roadmap	Ensure Phase-in and phase-out information	Ensure component CR validation timeline	Review commercial feasibility. Like Binding rules, and Ramp profile	Develop Validation and Sampling or Piloting Plan	Confirm readiness: Capacity and material
5. Monthly review of governance	Define forecast accuracy scale, horizon, frequency, and frozen	Materials segment such as long LT and configurable materials.	Ensure segmentation, including critical items and second sources.	Update on Porto and Pilot Sampling	
6. Release and approve forecast	Share Forecast to ESU Supplier	Share forecast to ECU supplier	Ensure commercial terms alignment	Approve and Sign PSW	Review forecast volume, Lead Time
7. Supplier order confirmation (monthly)	Ensure Order ESU supplier order confirmation	Ensure Order ECU supplier order confirmation		share technical compatibility and change clarification	Communicate Order Confirmation
8. KPI and performance management	Develop Accuracy metric, e.g. MAPE, Consumption, and Bias	Measure forecast accuracy metric	Identify the risk	Ensure BOM data, EOL status, and CR	Develop RC & CAPA, and participate in CIT meeting

Figure 19 presents a swimlane flowchart of the proposed forecasting process. It identifies key stakeholder groups and shows the sequence of activities in eight steps. This diagram clarifies the roles, responsibilities, and coordination needed for each stakeholder group, illustrating how the process promotes efficient collaboration and streamlined decision-making throughout the forecast.

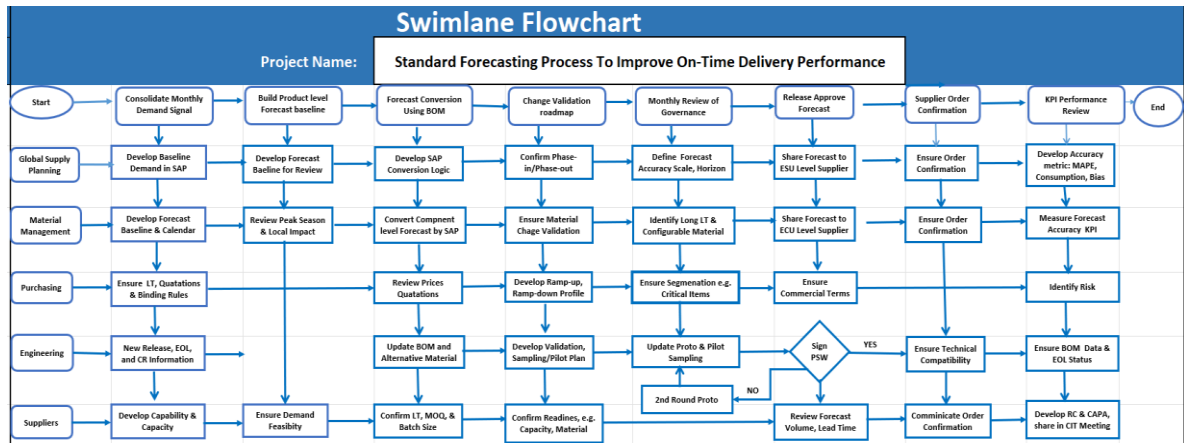


Figure 29: Swimlane Process Flowchart

5.5 Limitations of the Study

This thesis has several limitations that must be considered when interpreting the findings. First, the study collected qualitative and quantitative data only from European manufacturing units in Finland, Italy, and the Czech Republic. These findings do not directly apply to factories in other regions, such as Asia, the Americas, or China. Further research is needed to determine if the results are more broadly applicable.

Second, the study primarily focused on current forecasting practices and analyzed data from selected supplier cases, given the available data. This focus arose because forecast communication and OTD measurement did not cover all suppliers, as Supplier Quality Management does not follow all suppliers associated with the selected manufacturing units. Furthermore, other factors that affect supplier delivery performance, such as supplier capacity, geopolitical issues, geographical location, culture, transportation issues, and market uncertainty, were not analyzed.

Third, the quantitative analysis relied on historical data and key metrics: MAPE, RMSE, Forecast Bias, and Forecast Consumption. While informative, these metrics do not measure all aspects of forecasting accuracy and supply delivery. Additionally, the value of these results depends on the quality, consistency, and completeness of company data.

Fourth, the qualitative findings are based on interviews with selected internal stakeholders and suppliers. Although these interviews provide useful practical information, their response may reflect personal opinions and local views. Therefore, the qualitative findings should be regarded as illustrative examples from specific cases, rather than as completely objective measurements of the process.

Finally, this study did not include a comprehensive implementation evaluation of the proposed standard forecasting process. Although recommendations and a swimlane flowchart for improvement are presented, the study did not measure the long-term implementation in practice. Therefore, confirming the practical benefits of full standardization will require future implementation and follow-up.

5.6 Directions for Future Research

This study highlights several areas for further investigation. One direction is to examine whether the forecasting issues identified in European regions are also present in other regions. Another is to explore the relationship between forecasting results and supplier on-time delivery by considering factors such as lead-time variability, supplier capacity constraints, geopolitical issues, supplier location, transportation issues, and cultural factors. These investigations would help clarify which factors beyond demand forecasts affect delivery performance.

Future research could examine how using the same forecasting approach affects forecasting accuracy, cross-functional alignment, collaboration, supplier communication, and delivery reliability. Future studies might also investigate the effects of digital forecasting tools, automation, and data analysis in multi-location manufacturing sites.

Furthermore, future research could explore supplier collaboration, focusing on the forecast-sharing process, supplier feedback, and review-planning routines to influence forecast usefulness and delivery reliability.

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