Dealing with Supply Chain Complexities with Scenario Intelligence

by

Luis Felipe Bittencourt de Brito Sena
Bachelor of Science in Civil Engineering, State University of Goias, 2015

and

Zhan Ding
Ph.D., Bioengineering, University of Toledo, Toledo, Ohio, 2000

SUBMITTED TO THE PROGRAM IN SUPPLY CHAIN MANAGEMENT
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF APPLIED SCIENCE IN SUPPLY CHAIN MANAGEMENT
AT THE
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 2024

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Signature of Author: ____

Luis Felipe Bittencourt de Brito Sena
Department of Supply Chain Management
May 10, 2024

Signature of Author: ____

Zhan Ding
Department of Supply Chain Management
May 10, 2024

Certified by: ____

Dr. Maria Jesus Saenz
Executive Director, MIT Supply Chain Management Master's Program
Capstone Advisor

Certified by: ____

Dr. Devadrita Nair
Postdoctoral Associate, Center for Transportation and Logistics
Capstone Co-Advisor

Accepted by: ____

Prof. Yossi Sheffi
Director, Center for Transportation and Logistics
Elisha Gray II Professor of Engineering Systems
Professor, Civil and Environmental Engineering

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Luis Felipe Bittencourt de Brito Sena

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Zhan Ding

Submitted to the Program in Supply Chain Management
on May 10, 2024 in Partial Fulfillment of the
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ABSTRACT

The sponsor company, historically known for conventional cigarette sales, announced a commitment to a smoke-free environment in 2015. This strategic shift, combined with an increasingly volatile and uncertain environment, presented unprecedented levels of complexity to their inventory management process. Our project goal was to evaluate supply chain complexity through scenario simulations to recommend inventory management policies. The study began with a structured model using synthetic data simulating the sponsor company's supply and demand to gain insights into the behaviors of their complex supply chain. Through simulation, we identified the non-linear relationship between customer demand and the company's upstream inventory positions. With these insights, this project then simulated various forecast techniques and production plans using different safety stock methodologies such as Root Mean Square Error (RMSE), Standard Deviation of Forecast Error (SDFE), and Days of Inventory. Each policy yielded monthly simulated inventory positions, which were compared among themselves and with the company's real inventory position at the time. Furthermore, the paper evaluated the impact of reducing lead time by one month on their inventory cost. Our findings showed that using Exponential Smoothing with Damped Trend forecasting in time period *t* for period *t*+3 yielded a Mean Absolute Percentage Error (MAPE) of 20.7%, compared to the sponsor's current process which presented a MAPE of 28%. Moreover, the production plan methodology developed by this project would have presented 14% lower inventory cost to the company without any stockout event. Finally, a simulation tool utilizing the recommended production plan policy was delivered to the company enabling them to make scenario analysis for the future.

Capstone Advisor: Dr. Maria Jesus Saenz

Title: Executive Director, MIT Supply Chain Management Master's Program

Capstone Co-Advisor: Dr. Devadrita Nair

Title: Postdoctoral Associate, Center for Transportation and Logistics

ACKNOWLEDGMENTS

Luis: I would like to express my gratitude to advisors Dr. Maria Saenz and Dr. Devadrita Nair for their invaluable guidance, consistently steering us towards the best practices to be adopted in this project. A heartfelt thank you to my wife, daughter, mother, father, and whole family for their unwavering support throughout this endeavor. I extend my sincere appreciation to my partner Zhan Ding for our collaborative efforts during the months we worked on this project together. I also want to thank Professor Sean Willems for his mentorship and guidance throughout the project.

Thank you all for your contributions, which have enabled us to successfully complete this project, incorporating so many concepts.

Zhan: Completing this capstone project has been a challenging yet fulfilling journey, and I am deeply grateful to those who supported me throughout. First and foremost, I would like to express my heartfelt gratitude to my advisors, Dr. Saenz, and Dr. Nair, for their invaluable guidance, patience, encouragement, and inspiration. Your expertise and insights were instrumental in navigating this new subject matter.

I would also like to thank my capstone partner Luis Felipe who offered dedication, collaboration, and camaraderie.

A special thanks goes Mr. Antonio and the sponsor company, making this academic endeavor possible.

A final thanks goes to my wife, thank you for your patience and cheerfulness throughout this journey.

In loving memory of my dear dad, who sadly passed away during this time. Your spirit and wisdom continue to inspire me daily.

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1. Introduction

Our sponsor company Philip Morris International (PMI) was widely known as a cigarette company until 2015. Since then, they have announced to the world their goal to proactively contribute to a smoke-free planet. It means the sponsor company is building its future on smoke-free products that while not risk free are a better choice than cigarette smoking.

According to the company's Global VP of Supply Chain, in his speech at the Leaders in Supply Chain Awards 2023, in a short period of time, the sponsor company was able to increase the sales of smoke-free products, which now represent 39% of their net revenue as Q1'24. Their next milestone is to achieve 50% of their net revenues from the Heat not Burn (HnB) category by 2025. In addition to that, the sponsor company is entering markets for a variety of new categories, including e-cigarettes and nicotine pouches, further expanding their portfolio (Alcott Global, 2023).

The company´s VP of Supply Chain also stated in his speech that the organization has transitioned from a simple and stable product category, with a controlled manufacturing environment and a simplified distribution, to a more complex business. This complexity involves multiple product categories that are highly interconnected and are often competing for the same resources, like supply materials, manufacturing footprints, and distribution channels. Additionally, the complexity of the sponsor company's portfolio has increased by 100% over the last three years and is expected to double again in the next three years (Alcott Global, 2023).

1.1 Motivation

In addition to the company's strategic shift, the recent escalation of the VUCA (Volatile, Uncertain, Complex, and Ambiguous) world has introduced unprecedented levels of complexity to businesses, including our sponsor company. Within this challenging landscape, the supply chain process plays a critical role in translating the company's vision into reality.

Furthermore, the fact that the company is changing its strategy and rapidly growing in a new product segment is adding complexity to its supply chain, as it transitions from a category of simple and stable products to one that encompasses a broader range of offerings in a new segment, where they compete for the same resources. Therefore, in this scenario, the company has less accuracy in forecasting, as it has less information to make its predictions and the market is not as stable as that of conventional cigarettes. In this context, the company may experience a higher-than-expected Loss of Goods Sold, referred to internally as LOGD.

1.2 Problem Statement and Project Questions

Given the growing necessity to manage supply chain uncertainties in this complex environment, this project aims to provide the sponsor company a recommendation on the inventory management policy, through simulation exploring how different scenarios may impact the company, by considering fluctuations in demand, lead time extensions, increased lead time variability, and adjustments in target service levels. In this context, the questions to be answered include:

1. How can the application of simulation enable the company to conduct scenario analysis effectively to address the complexities within their supply chain process?
2. What is the recommended inventory policy for the company?
3. How might different scenarios affect the company´s inventory position?

1.3 Scope: Project Goals and Expected Outcomes

The simulation model will be based on data ranging from January 2021 to November 2023 from the region the sponsor company refers to as the CZ Cluster, which includes the Czech Republic, Hungary, Poland, and the Slovak Republic, for products Heets and Terea, which are two different categories of Heat not Burn products. This project will focus on the demand side of their supply chain process and deliver managerial recommendations on the inventory management policy for the sponsor company to adopt. Additionally, the project will deliver a simulation tool that will allow the company to conduct scenario analysis for the future.

1.4 Project Plan of Work

To provide recommendations for the company's inventory policy and construct the simulation model, the first step was to understand the company's current supply chain process.

Upon receiving the historical data containing forecast information, actual sales data, and inventory levels for the products and markets under analysis, the data cleaning and data analysis stage was initiated to prepare the data for the simulation models.

After collecting and cleaning the data, various production plan policies using different safety stock methodologies were evaluated to compare their potential impact on the company's inventory position. The inventory levels yielded by these methodologies were also compared with the company's historical stock positions. Following the analysis and comparison of the results, our inventory management policy recommendation was formulated, and based on this recommendation, a simulation tool was developed to allow the company to conduct scenario analysis for the future.

2. State of the Practice

The aim of this project is to provide recommendations for the inventory policy of the sponsoring company. In this section, we will begin by examining factors that contribute to the complexity of the company's operations. Additionally, we will explore the product diffusion curve across various industries. Subsequently, we will explore different forecasting techniques to be utilized in this project. Finally, we will introduce the concept of the Period Review Policy, which will inform the development of production plans in simulation models.

2.1 The Complexity

The complexity as shown in Figure 2-1 in the tobacco industry's inventory forecasting models requires a critical reassessment, particularly considering the integration of both exogenous and endogenous factors. These models, traditionally reliant on historical data and tailored for legacy products, may fall short in the face of market disruptions. Exogenous factors such as regulatory changes and shifting consumer behaviors, along with endogenous factors like production processes and internal supply chain dynamics, necessitate a thorough reevaluation and adaptation of these models. This strategic update is essential to ensure their relevance and effectiveness in navigating the evolving market dynamics, thereby maintaining operational efficiency and a competitive edge in a rapidly changing industry landscape.

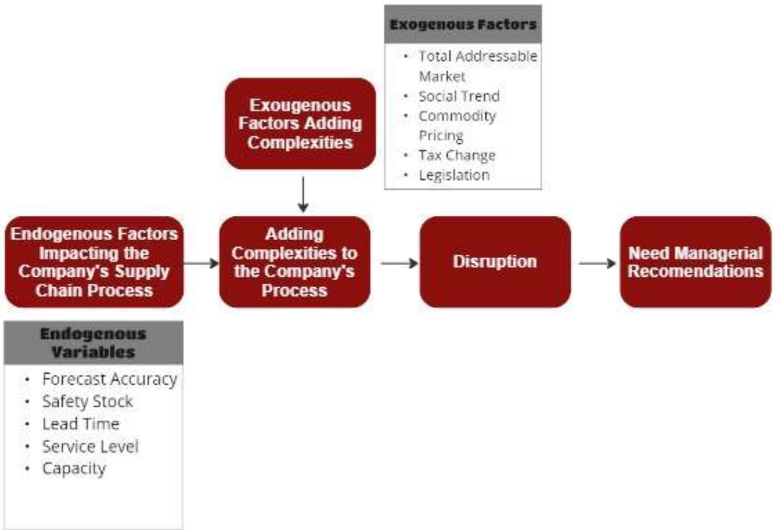
2.1.1 The Industry

The tobacco industry operates within stringent regulatory frameworks, necessitating strict adherence to laws that govern various aspect of industry, including advertising, packaging, and sales, with a focus on public health initiatives that can significantly vary across different markets.

These regulations dictate strict timelines for sales and product disposal, requiring companies to discard goods that could be consumed but for a certain reason do not match the regulatory requirements anymore.

Figure 2-1

The Sponsor Company Supply Chain Complexity Involving Exogenous Factors Such as Global Forces and Endogenous Focus Areas



Notes. Recent expansion of the portfolio and increasing complexities in worldwide supply chain is testing the commercial, operational, financial processes highlighting risks and resiliency gaps for many organizations. Some examples of major disruptions, 1. Logistic disruption; 2. Production delays; 3. Third parties/suppliers' reliability; 4. Commodity pricing; 5. Workforce and labor.

2.1.2 The Forward-Coverage Forecasting Method

The sponsor company is confronted with another complexity: enhancing their forecasting methodology, particularly within the emerging HnB category, which introduces its own complexity that involves different behaviors in depending on the market channel.

In their comprehensive analysis, Neale & Willems (2014) provided a detailed explanation of the forward-coverage model, highlighting its intuitive adaptability to demand fluctuations and its mathematical defensibility. This approach is widely adopted by a variety of known companies due to its effectiveness and practicality, and so is by the sponsor company. While the forward-coverage model is widely adopted, it can cause the so-called landslide effect, which is very similar to the challenges the sponsor company is facing.

The landslide effect in inventory management refers to a phenomenon where small changes or errors in inventory planning and forecasting lead to disproportionately large fluctuations in inventory levels. This effect can result in costly overstocking or stockouts, negatively impacting operational efficiency and profitability.

The landslide effect underscores the importance of accurate demand forecasting, robust inventory planning, and effective supply chain management practices. By minimizing errors and uncertainties in inventory management processes, companies can mitigate the risk of experiencing the detrimental effects of the landslide effect and maintain optimal inventory levels to meet customer demand while minimizing excess inventory costs.

2.1.3 The Nonlinear Dynamics in Operations

For complex business operations, business dynamics and system thinking are critical (Sterman, 2010). Coordinating a set of departments under various constraints and uncertainties is a complex problem, primarily due to ambiguity in determining component requirements, uncertainty in component services, and interdependencies among services. Addressing these challenges requires finding ways to achieve coordination and coherence among supply chain partners, (Latifa et al., 2013).

Ashayeria & Lemmes (2006) believed global business and markets are evolving into unpredictable, fragmented, and dynamic environments. Instead of relying solely on static analyses of aggregated data, stakeholders must navigate the changes by selecting the optimal model that allows for more accurate and responsive demand planning in the face of evolving market conditions.

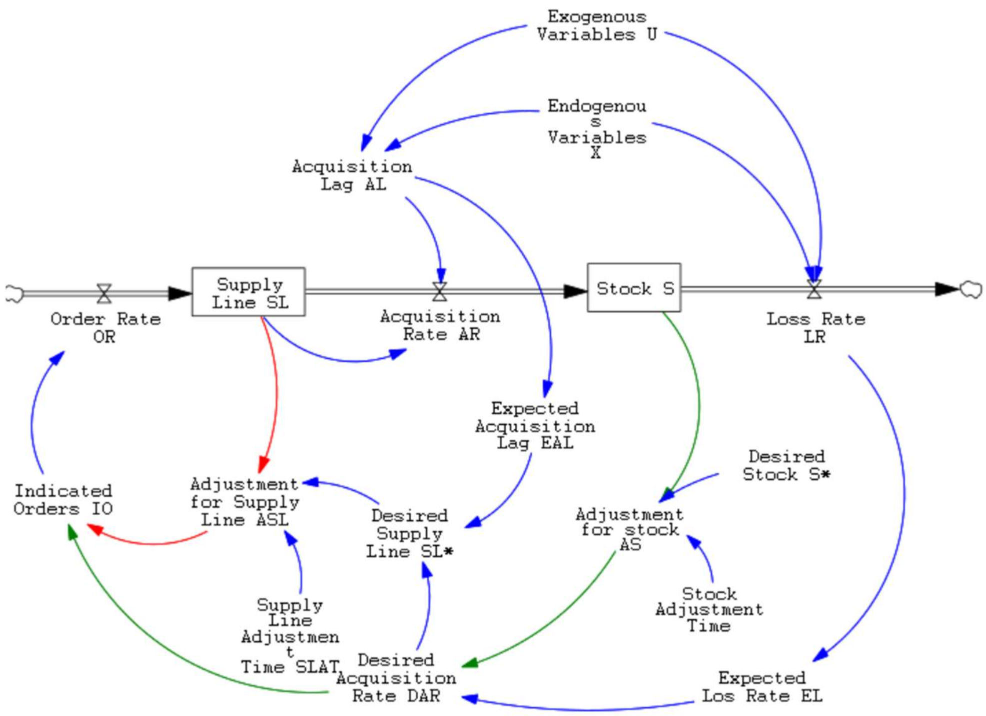
Based on the analytical data, various techniques are commonly employed for scenario planning. These include the Monte Carlo Simulation (Metropolis & Ulam, 1949), Discrete Time/Event (Navonil et al., 2021), Agent Based Simulations (Dhanan et al., 2017), and System Dynamics (Sterman, 2010). System Dynamics modeling is particularly useful for capturing the nonlinear behaviors of complex systems (Sterman, 2010), incorporating reinforcing or balancing feedback loops to comprehend system dynamic behavior.

System Dynamics effectively models complex systems by breaking them down into state variables without losing the essence of the system's true nature. This modular approach starts with a simple framework, allowing modelers to gradually expand into more detailed, manageable modules. By mapping each module’s attributes to physical settings, previously unknown problems can be redefined and addressed using established knowledge. This method transforms challenging, undefined scenarios into structured, solvable problems, providing a clear pathway through the lens of familiar concepts. John D.

Sterman (2010) outlines in his book "Business Dynamics – System Thinking and Modeling for a Complex World" a generic model Figure 2-2 for supply chain management, which serves as an illustrative example.

Figure 2-2

Adapted From Demands, Capacity and Exogenous Factor Increasing Inventory Planning Complexity



This model includes exogenous and endogenous variables, delves into the dynamics of supply pipeline and stock levels, offering a foundational understanding of key considerations. Firstly, it underscores the multitude of factors and variables that companies must weigh when managing supply line lead time or stock levels. It emphasizes that merely ordering new units to replace consumed ones can be problematic; instead, companies must account for existing inventory within the supply pipeline (depicted by the red loop). This necessitates minimizing the gap between desired and actual supply line performance (red loop) or stock levels (green loop) by adjusting procurement based on anticipated needs—a process that can involve various estimation techniques, as elaborated in subsequent sections.

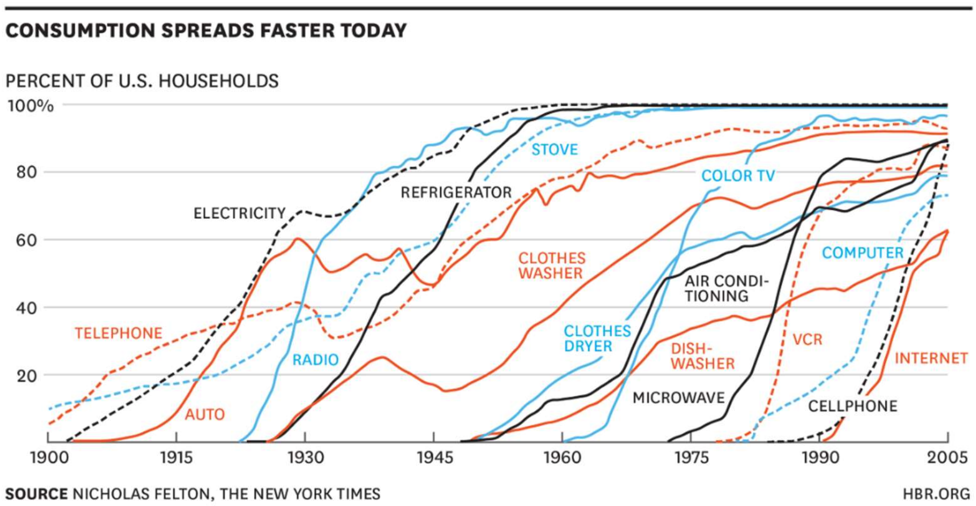
Secondly, the adjustment of stock presents challenges, given its irreversible nature once products are manufactured. In contrast, tweaking supply pipeline configurations is relatively more flexible than acquiring new units, making it a pivotal focus for addressing the complexities of supply chain management.

2.2 Product Diffusion

Considering the sponsor company's goal of increasing sales in the HnB category, it is beneficial to introduce the Bass Diffusion Model outlined in Figure 2-3. Simply speaking, the Bass Diffusion Model, widely employed across strategy, marketing, and diverse domains, elucidates the trajectory of product adoption through an S-shaped growth curve exhibited by many products shown in Figure 2-3. A deeper comprehension of the adoption curve could assist companies in selecting inventory simulation models with appropriate assumptions.

Figure 2-3

Rate of New Product Adoption



Note. From "Consumption Spreads Faster today" by Nicholas Felton, 2007, The New York Times.

One of significant instances of S-shaped growth is referred to as logistic growth (Richardson, 1991). The logistic growth model (1) postulates that the net fractional population growth rate is a downward-sloping linear function of the population, to estimate the new product adoption growth curve. Ultimately, the model suggests that no growth is infinite—once the total population capacity is approached, the system's expansion stabilizes and shifts toward equilibrium, marking a transition to dominance by negative feedback as the product reaches market saturation.

$$\ln\left(\frac{A}{P}\right) = ln\left(\frac{A(0)}{P(0)}\right) + g_0 t \qquad (1)$$

Notation:

A: number of adopters (the installed base), A(0) is the initial adopters

P: Potential population, P=N-A, where *N* is the Carrying Capacity or the Total Population *N* in Figure 2-4, P(0) is the initial potential population.

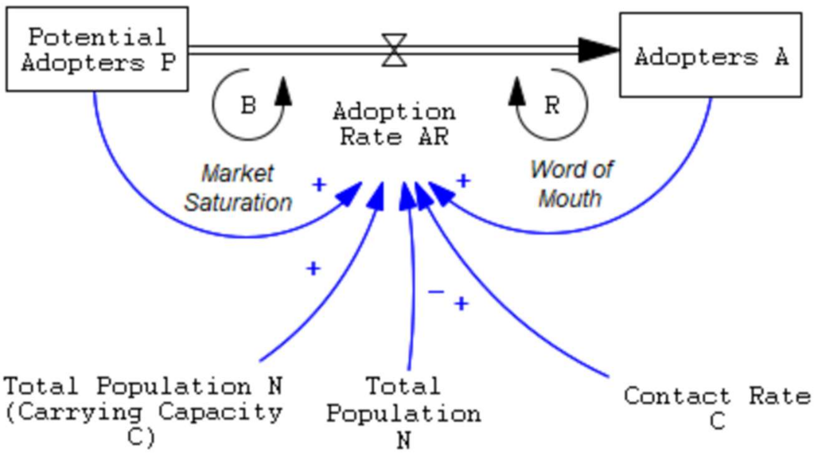
g_0: initial fractional growth rate

t: time units

Viewing it through the lens of System Dynamics modeling, the logistic growth unfolds as Figure 2-4.

Figure 2-4

The Logistic Growth Diffusion Model



Note. Adapted from "Business Dynamics System Thinking and Modeling for a Complex World" by John D. Sterman, 2010.

The logistic growth features two feedback loops: a balancing loop denoted as 'B' and a reinforcing loop marked as 'R' in the diagrams, driving the adoption process. The balancing 'B' loop is fueled by mass media efforts from companies, aimed at raising product awareness among potential adopters. As adoption increases, the pool of potential adopters diminishes, which in turn reduces the impact of further marketing effects. This represents a natural limit to growth as the market becomes saturated. In contrast, the reinforcing 'R' loop operates through social influence within personal networks. As more individuals adopt the product, they create more exposure and endorsements for it, thereby increasing the probability that non-adopters will convert to adopters. This loop tends to accelerate adoption.

It is worth noting that researchers are continuing to refine the basic diffusion model from the Bass diffusion model, aggregation modeling techniques to extending into individual-level models (Ranganath, 2012). Within product category forecast, if there is a need to forecast between products within families, Norton and Bass (1987) model which is the extended version of Bass Model can be useful to capture the cannibalization effect of successive products.

2.3. Forecasting

Forecasting techniques can broadly be classified into subjective and objective categories. Subjective techniques often result from collaboration across various company departments, such as sales, marketing, market intelligence, and finance. These methods draw on collective expertise and insights from different areas of the business. Subjective forecasting itself divides into judgmental methods based on the internal knowledge and opinions from sales force surveys and expert insights, and experimental methods, which gather external feedback via customer surveys or focus groups. Conversely, objective forecasting is primarily in the domain of production and inventory planners. This approach is categorized into causal methods that seek to uncover underlying relationships and time series methods aimed at identifying demand patterns using techniques such as moving average, exponential smoothing, damped trend analysis, regression, machine learning predictions, among others (Caplice & Ponce, 2023).

2.3.1 Moving Average

A moving average method is a time series forecasting technique, which operates by averaging consecutive values from a dataset to smooth fluctuations and highlight underlying trends. This approach is categorized within the broader scope of filtering techniques, which convert an original time series into a modified version by successively recalculating averages to include new data while excluding the oldest data points. This ensures an up-to-date reflection of the series with a consistent number of data points in each average, facilitating a clear analysis of trends over time.

The moving average method, however, is characterized by its selectivity in the number of data points considered for each average. For instance, a 6-point moving average would only incorporate the six most recent data points, equally weighted, to compute the average. This specificity in the selection of data points allows for tailored analysis and forecasting, adaptable to various analytical needs and time frames (Makridakis et al., 1998).

The moving average equation is according to (17) in the Appendix Section D.1.

2.3.2 Exponential Smoothing for Level and Trend (Holt Model)

Exponential smoothing for Level and Trend, also known as Holt´s Model assumes a linear trend and stands out from methods such as Cumulative, Naïve, and Moving Average by adjusting the importance of data based on its proximity in time. This method is based on the concept that data points closer to the present are more significant due to their timeliness, and their relevance decreases exponentially as they age. In essence, exponential models seamlessly integrate information from the near past with more dated data.

The emphasis on newer data relative to older data is controlled by the alpha factor, with a range from 0 to 1. This parameter sets the balance between new and old information, by defining how much weight is given to the latest observations in the model. When the alpha factor is near to 1, the model's forecast aligns more closely with the naïve method. When the alpha is close to 0, the forecast resembles the cumulative method more closely. Typically, in practical applications, the alpha factor is selected within the range from 0.1 to 0.3. The equations for this methodology are according to (18), (19) and (20) in the Appendix Section D.2 (Caplice & Ponce, 2023).

When combining the Exponential Smoothing method with RMSE (Root Mean Square Error) in forecasting, we have the capability to variably weight errors over time. In this approach, recent errors are given more significance than older ones, mirroring the principle of Exponential Smoothing. This differential weighting is facilitated through the adjustment of the omega parameter, known as the Mean Squared Error Trend, specifically designed to prioritize recent forecast errors.

2.3.3 Damped Trend Model with Level and Trend

Recognizing that trends do not persist unchanged indefinitely and that assuming constant linear trends can result in over forecasting, the damped trend model emerges as a suitable recommendation for longer forecast horizons. It aims to more accurately mirror the diminishing effect of trends observed in real-life scenarios. This model introduces a minor adjustment to the exponential smoothing model by incorporating a dampening parameter, phi (ϕ), with values ranging between 0 and 1. This parameter effectively moderates the projection of trends over time, ensuring that forecasts become more conservative as they extend into the future. The equations for this methodology are according to (21), (22) and (23) in the Appendix Section D.3 (Caplice & Ponce, 2023).

2.4. Inventory Model – Periodic Review Policy

In today's fast-paced business environment, efficient inventory management stands as a cornerstone for organizations aiming to meet customer demands while optimizing operational costs. Within the spectrum of Multi-Period Inventory Models, which includes methodologies like Economic Order Quantity, Single Period (News Vendor), Base Stock Policy, Continuous Review Policy, and Periodic Review Policy, the latter has been chosen for this project. This decision stems from its alignment with the sponsor company's operational reality, where production planning occurs monthly. This monthly cadence is necessitated by the need to meticulously coordinate labor, raw material availability, production mix, and other variables in advance. Therefore, our focus in this topic will be dedicated to addressing the key considerations relevant to this inventory policy.

The quantity of units that the company will order up to this number, known as S, can be calculated according to (2), which states that the company will maintain an inventory target capable of fulfilling the expected demand along with a safety stock.

$$S\ (units) = \mu_R + k\sigma_{L+R}, \tag{2}$$

The safety stock represents the level of inventory necessary to mitigate the probability of the company experiencing stockouts to a degree less than the Cycle Service Level. For instance, if a company's Cycle Service Level is 95%, then the safety stock denotes the quantity of inventory the company should maintain to cover over 95% of the expected units to be sold during the replenishment cycle (Caplice & Ponce, 2023).

When developing an inventory model for the future, particularly in scenarios where a company depends largely on forecasts rather than historical data, the forecasted demand for the period serves as the mean value and the root mean square error (RMSE) of the forecast error over that specific timeframe is used along with the service level, lead time, and review period to calculate the review period (Caplice & Ponce, 2023).

3. Methodology

After a literature review on different methods of inventory optimization policies and different forecasting approaches, these methodologies will be put into practice using the information provided by the company for the four markets and the two products under analysis. Scenarios will be created to compare how different production plans stack up against each other and against the actual inventory curve of the company from December 2021 to November 2023. Comparisons will also be made with the mathematical forecasting models discussed in the State of the Practice section, alongside the current forecasting model of the sponsor company.

3.1 Data Gathering and Analysis

3.1.1 Data Gathering

The company provided us with two sets of data: one containing the historical monthly forecast and monthly sales for the products and markets under the scope of this project ranging from 2021 to 2023, and another dataset containing the company's weekly inventory position for the same products (two main products under the Heat not Burn category) and the four markets under the scope of this project.

The dataset containing monthly forecasts and actual market sales presented different forecasting versions. Therefore, data processing was necessary to ensure that the production plans considered in the simulations of this project were based on the most updated forecast at the time of production plan execution, mirroring the approach taken by the company during the same period.

Data treatment was also necessary for the dataset containing the company's weekly inventory position. We received the data on a weekly basis, but the relevant information for our simulation was only the last monthly inventory position per product and per market.

3.1.2 Data Analysis

As HnB represents a new ~~novel~~ product category, our initial step involves comprehending their diffusion into the market and validating whether they adhere to (1).

The decline in Heets sales (orange line) observed in January 2023 can reasonably be attributed to the company's launch of the second-generation product, Terea (grey line). It's plausible that some HnB users transitioned from Heets to Terea, resulting in the drop in Heets sales. However, the overall user population appears to continue growing, as shown in Figure 3-2 below, indicating a diffusion growth trend.

Figure 3-1

Heets and Terea Sell in Data in Czech Republic

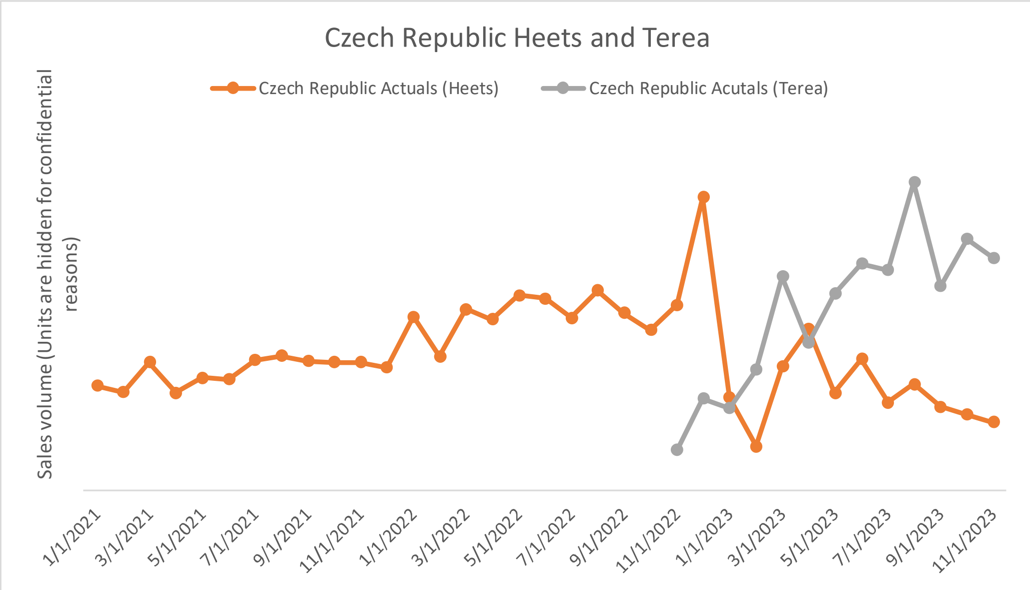
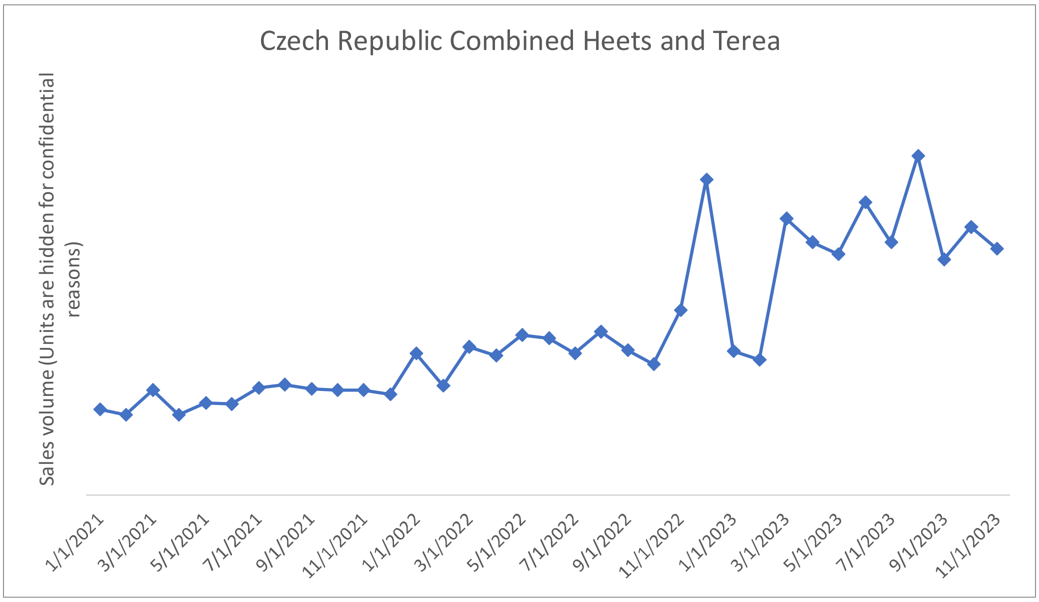


Figure 3-2

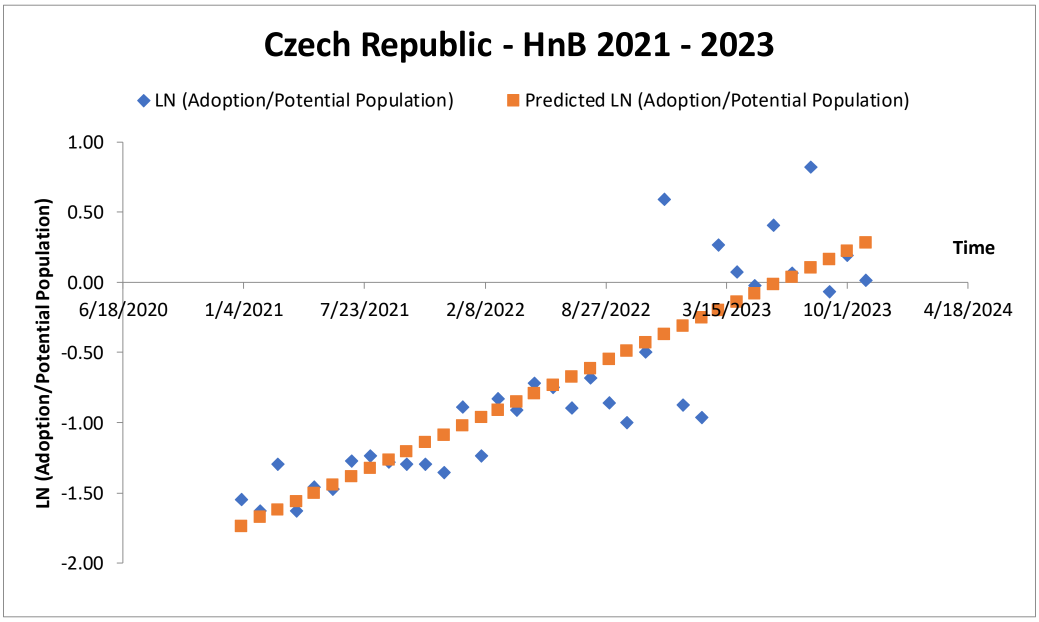
Combined Heets and Terea Sell in Data in Czech Republic



To understand where HnB fit within the Bass diffusion curve, logistic regression analysis was conducted, and the Czech Republic is shown as an example in Figure 3-3 which uses (1) defined for this purpose. Additionally, the regression results are summarized in Table 3-1. The analysis revealed a high R-value of 0.79 that is statistically significant. These findings allow the study to treat the data as representing a single product category, simplifying the data analysis, and modeling process. Similar data analysis has been conducted for Hungary, Poland, and Slovak Republic as well, which are available in Appendix A.

Figure 3-3

Fitting the Logistic Growth (1) to Data for Czech Republic for HnB Adoption Over Addressable Population



Note. In Figure 3-3, we assumed that the Original Budget (OB) represented the company's estimation of the market and was used as the carrying capacity.

Table 3-1

Fitting the Logistic Growth (1) to Sales Data for Czech Republic for HnB Adoption Over Addressable Population Regression

R Square	*Adjusted R Square*	*Coefficients (intercept)*	*Coefficients (Time)*
0.79	*0.77*	*-38.27****	*0.00081****

In the analysis described, the study utilizes the sponsor company's Original Budgeting (OB) estimates as the proxy for the sponsor company's market carrying capacity. To mitigate potential biases from relying solely on first-party data, the analysis was also extended to encompass overall market data, including third-party products shown in Table 3-2. When adapting the data to include these third-party and total addressable market figures, we observed similar patterns that were statistically significant across the four markets studied. Notably, all markets demonstrate a modest growth slope, indicating that they are transitioning into a period of mature growth.

Table 3-2

Fitting the Logistic Growth (1) to market data of Czech Republic, Hungary, Poland, and Slovak Republic.

	Czech Republic	*Hungary*	*Poland*	*Slovak Republic*
Multiple R	*0.89*	*0.85*	*0.98*	*0.84*
R Square	*0.79*	*0.72*	*0.95*	*0.71*
Adjusted R Square	*0.77*	*0.70*	*0.95*	*0.70*
Intercept	*-38.27****	*-54.84****	*-63.18****	*-43.47****
Slope	*0.00081****	*0.0012****	*0.0014****	*0.00093****

3.2 Simulation Model for Manufacturing Scenario Planning

The dynamic, non-linear supply chain system we learned from the sponsor company comprises inflow, such as production at discrete monthly intervals, inventory in pipeline and channels, and the continuous outflow of product consumption. A useful equation for simulating this complex and dynamic inventory considering production happening on a monthly cadence and consumption being ongoing, can be derived from understanding the balance between these two flows over time. This approach typically integrates the production and consumption rates over the same period to predict inventory levels. To begin, the paper defines the inventory level *I(t)* at any time *t* can be modeled by the (3):

$$I(t) = I(t-1) + f(t) - g(t) \tag{3}$$

Notation:

f(t): batch product releases at discrete monthly intervals.

g(t): continuous consumption.

I(t-1): the inventory at the end of previous period.

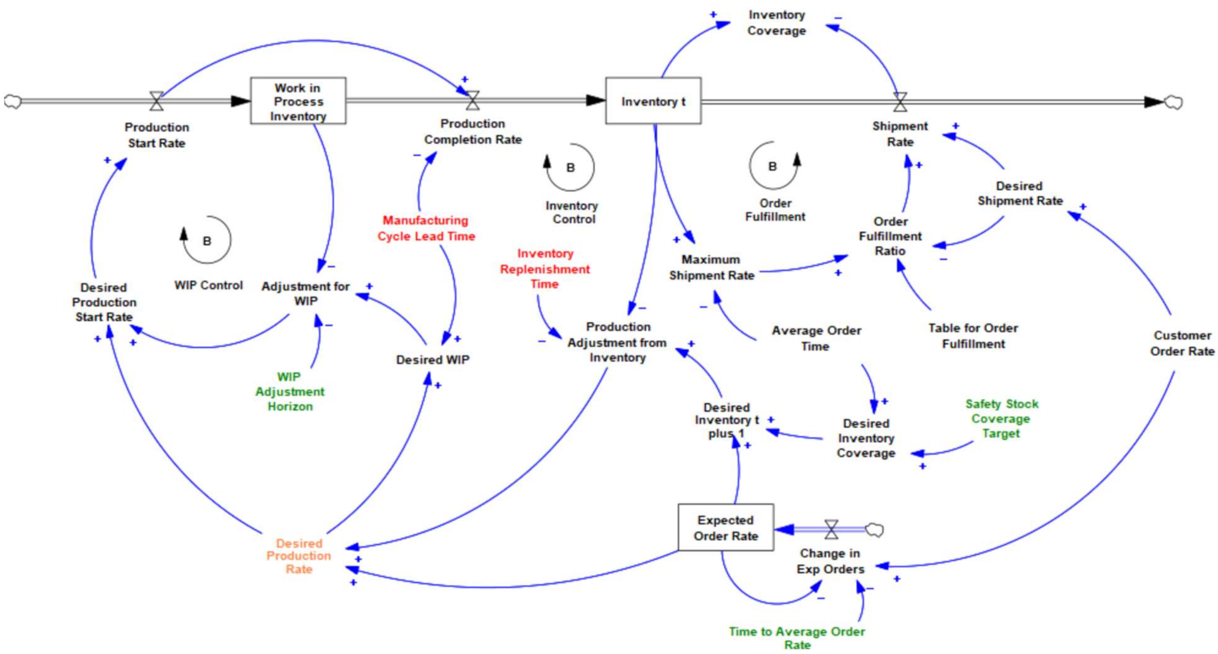
According to the data analysis discussed in Section 3.1.2 of the paper, the product category exhibits modest growth, leading to the assumption that the consumption, denoted by *g(t),* remains relatively stable. Therefore, this paper explores various scenarios for production, denoted by *f(t),* using forecasting techniques such as the Moving Average, Holt Model, and Exponential Smoothing with Damped Trend. The objective is to assess the efficacy of these methods in predicting production needs while considering safety stock levels.

The paper utilizes a System Dynamics framework for manufacturing inventory management, as illustrated in Figure 3-4. The primary advantage of using this simulation model is its ability to provide detailed insights into the key drivers of inventory levels and production efficiency. By adjusting various parameters within the model, we can simulate different operational scenarios, which helps identify leverage points where changes yield the most significant improvements.

Specifically, the simulation assists in understanding how changes in production rates, lead times, and demand variability affect overall inventory levels and service levels. This insight is crucial for the paper in later section for optimizing production, inventory, and minimizing costs associated. Detailed results from these simulation scenarios are comprehensively documented in Appendix A.

Figure 3-4

The Structure of Inventory and Production



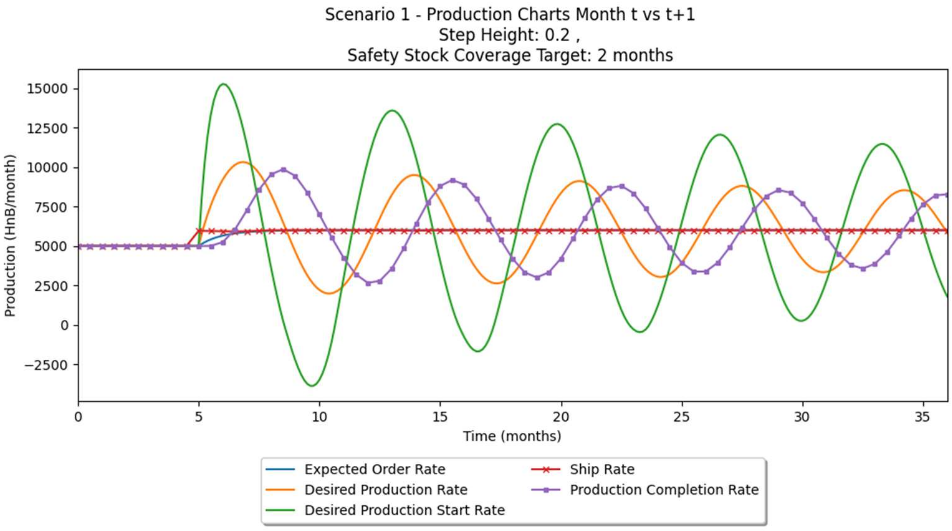
Note. Adapted from Business Dynamics System Thinking and Modeling for a Complex World by Sterman J.D, 2010

For example, in Scenario 1, the model starts in an equilibrium state where all flows, including the Production Completion Rate and Shipment Rate, remain constant until time unit 5, as depicted in Figure

3-5. Starting at time unit 5, a single step increase of 20% in the Shipment Rate is introduced, with the resulting dynamics shown in Figures 3-5 and Figures 3-6. This change triggers the system to dynamically respond through a series of interconnected feedback loops, inventory adjustments, and flows that mimic real-world operations in Figure 3-4, resulting in a much larger amplification compared to the initial demand increase for flow rates throughout the system.

Figure 3-5

Simulation Scenario 1 of Production Level Oscillation Due to Ship Rate Increased by 20%



Note. Simulation scenario before time unit 5 are in equilibrium state where inflows and outflows are constant. Starting at time unit 5, a single step increase of 20%.

Observations from Figure 3-5 and Figure 3-6 underscore critical system behaviors, particularly the system's efforts to reach equilibrium, often leading to undesirably high inventory levels. While it naturally tends to minimize amplification, the company must carefully weigh policy decisions and trade-offs to ensure adequate service levels are met. In the same scenario, illustrated in Figure 3-6 and detailed in Figure 3-7, serviceability falls below 100% on five occasions throughout the simulated period.

Figure 3-6

Simulation Scenario *1 of Inventory and Service Oscillation Due to Ship Rate Increased by 20%*

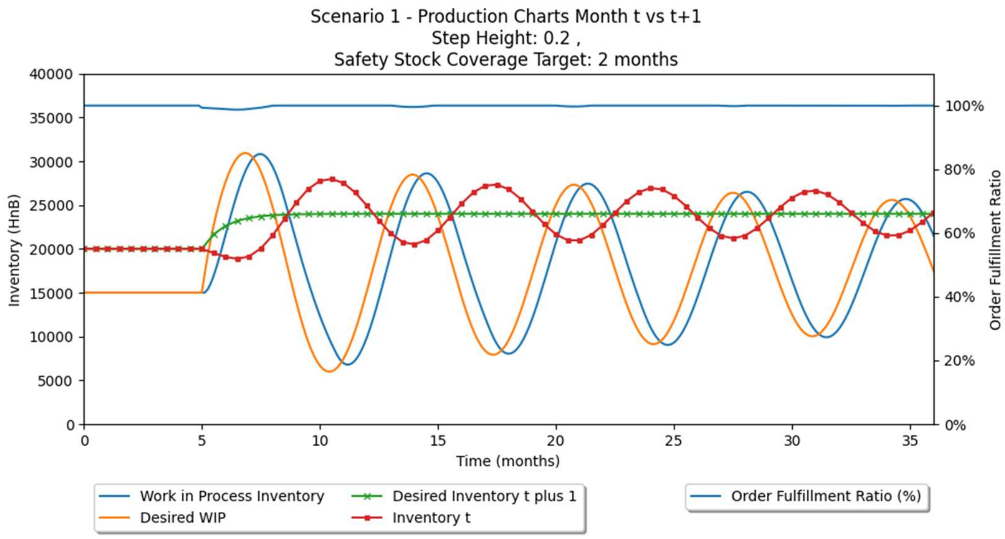
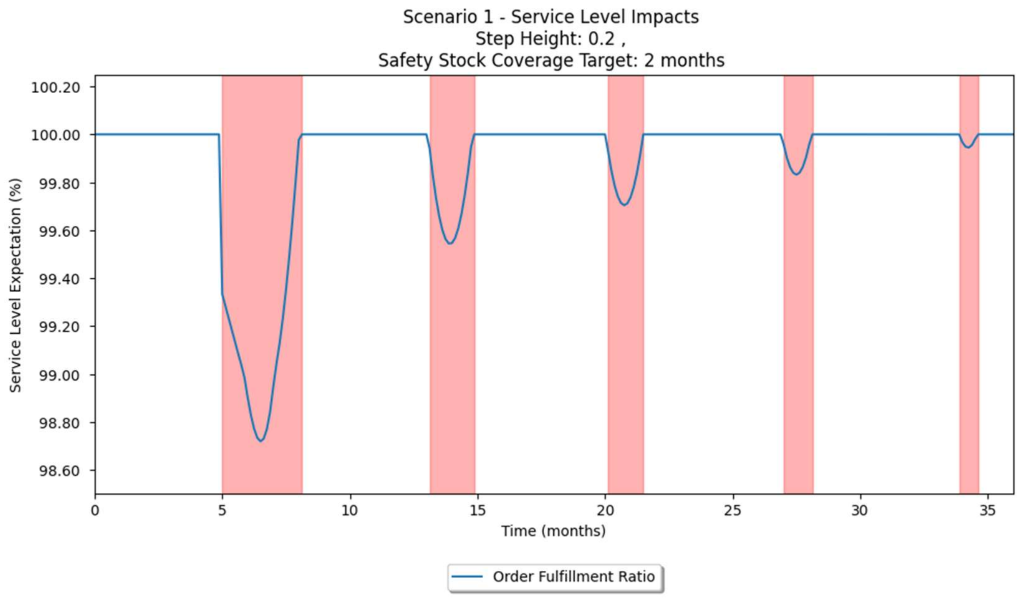


Figure 3-7

Simulation Scenario 1 of Service Level below 100% Due to Ship Rate Increased by 20%



3.3 Inventory Optimization Model – Comparing Different Forecasting Techniques

This study employed various forecasting methodologies, such as Moving Average, Exponential Smoothing Holt Model, and Holt Model with Damped Trend. The aim was to analyze how these forecasting models performed by comparing them with the company's forecast to provide recommendations regarding the forecasting process to the sponsor company. Initially, these models were analyzed considering forecasting for time period *t+1* in time period *t* to understand the results these mathematical models are yielding in a moment that typically exhibits the best outcomes, which is forecasting for the next time period. However, for production planning execution, it's necessary to consider that the company is in time period *t-1*, forecasting for time period *t+L*. Thus, considering a lead time of 2 months, we assessed the forecasting methodology of Damped Forecasting, as this model can forecast for the future through a trend while simultaneously considering a factor to dampen this trend. The Moving Average methodology is unable to consider this trend.

With these analyses, we were able to compare how different forecasting techniques performed in their best-forecast window (predicting for the next period) and when predicting 3 months ahead, comparing the results with the current process of the sponsor company.

This section, focused on the forecast results of the Exponential Smoothing with Damped Trend methodology, as it is capable of making predictions for future months considering a level, a trend and a factor to damp the trend, which is important when conducting long-term analysis, and is more aligned with the reality of the sponsoring company. The results of the other forecasting analyses will be presented in Appendix B for the company to observe how these models would perform if the company manages to reduce the forecast window, for example, by reducing the lead time.

3.3.1 Forecasting Metrics

There are different metrics to assess the quality of a forecast, such as Mean Deviation (MD), Mean Absolute Deviation (MAD), Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Percent Error (MPE), and Mean Absolute Percent Error (MAPE). In this work, as we intend to assess the forecasting quality in percentage terms, we will use Mean Absolute Percent Error (MAPE) as a comparison metric. MAPE is calculated according to (4), where *At* is the Actual Result and *Ft* is the Forecast for time period *t*.

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|At - Ft|}{At}}{n} \tag{4}$$

3.3.2 Exponential Smoothing Damped Trend Forecast – Forecasting for *t+3* in Time Period *t*

In this scenario, forecasting for time period *t+3* while in time period *t* was considered. Thus, the forecast is obtained through the following equation, where a_t and b_t are found according to (19) and (20) respectively.

The equation for this method is defined according to (5).

$$X_{(t,\, t+3)} = a_t + 3 \cdot \varphi \cdot b_t \tag{5}$$

This model presented an Accumulated MAPE of 20.7%, compared with 28% of the company current forecasting process, detailed in Table B-6 in Appendix B.

3.4 Inventory Optimization Model – Comparing Different Production Plans

To recommend the optimal inventory policy for the company, we developed five distinct production plans policies employing different safety stock methodologies. These plans were scaled for the company's two products across four different markets and then compared against each other and the actual inventory position observed from December 2021 to November 2023.

To efficiently assess the performance of these production plan policies, we consolidated forecasts, actual sales and stock positions across all markets and products, resulting in an aggregated production plan policy. This streamlined approach allows for easier interpretation, analyzing the performance of the production plans within a unified scenario, rather than scrutinizing eight separate charts and metrics. This analysis guided our recommendations for the company's production plan policy.

3.4.1 Production Plan Utilizing a Standard DOI (Days of Inventory) Target

This policy is the most similar to the one the company is currently using. Based on factors such as lead time, agreements with distributors, the importation process, and others, the company sets a number of days of inventory that it believes will provide security to the process to prevent stockouts, while also ensuring that the market is not left with an excessive surplus of product. Figure F-1 displays a chart with the inventory position for the Days of Inventory methodologies.

Under this policy, the company's safety stock is calculated according to Equation (6).

$$Safety\ Stock_x = DOI_x * Daily\ Average\ Forecast_x \tag{6}$$

Notation:

$Safety\ Stock_x$ = target safety stock in units for the company to maintain by the end of the month *x* (units)

DOI_x = target days of inventory for the company to have by the end of the month x (days)

$Daily\ Average\ Forecast_x$ = daily average sales projected for *x* upcoming months (units)

The $\text{Daily Average Forecast}_\text{x}$ is not the quantity of units the company expects to sell per day in month *x*. Rather, it represents the number of units per day the company anticipates selling in the months following month *x*. Therefore, by multiplying the desired number of days for safety stock by the daily unit sales expected in subsequent months, the company determines the target safety stock it aims to have at the end of month *x*. The Daily Average Forecast in this project, was calculated according to (7).

$$Daily\ Average\ Forecast_x = \frac{Monthly\ Sales\ Forecast_{x+1} + Monthly\ Sales\ Forecast_{x+2}}{60}, \tag{7}$$

In (5), the Monthly Sales Forecast represents the quantity of units the company forecasts to sell in the respective months.

With the calculation of the safety stock, the original production plan for the month *x* is calculated according to (8).

$$\begin{aligned} Production\ Plan_{(x-1,\ x,\ x+L)} = Monthly\ Forecast_{x+L} + Safety\ Stock_x \\ -Ending\ Inventory\ Position_{x+L\ -1} \end{aligned} \tag{8}$$

Notation:

$Production\ Plan_{x-1,x,x+L}$ = is the production plan to be made in month *x-1*, for the following month, which will reach the market L months after the month in which it was produced (units)

$Monthly\ Forecast_{x+L}$ = the monthly forecast to be sold in the month *x+L* (units)

$Safety\ Stock_x$ = the calculated safety stock using the DOI methodology, according to the (3-2) (units)

$Ending\ Inventory\ Position_{x+L-1}$ = simulated inventory position from the month prior to the month in which the product will reach the market (units)

When assessing the performance of various production plans against historical outcomes or developing simulation models with stochastic demands to evaluate different strategies for the future, incorporating forecast errors in the inventory position is crucial. This approach provides a more accurate reflection of real-world conditions. Since production plans aim to adjust the market supply based on the difference between the previous month's ending inventory and the forecast for the upcoming month, plus safety stock, the model assumes that actual demand aligns with the forecast. This assumption simplifies the calculated ending inventory position for month *x* to always represent the safety stock. However, for a meaningful evaluation of inventory policies and their comparison to the company's actual historical inventory, acknowledging forecast error is essential. Ignoring this leads to comparisons between theoretical desired inventories and actual inventories affected by past forecast inaccuracies. To address this, a production plan that considers forecast error needs to be defined according to (9).

$$Production\ Plan\ with\ Forecast\ Error_{\ (x-1,\ x,\ x+L)} = Forecast_{x+L} + Safety\ Stock - Ending\ Inventory\ Position + Monthly\ Forecast\ Error_{x-2} \tag{9}$$

In this equation, the $Monthly\ Forecast\ Error_{x-2}$ represents the most recent forecast error, occurring in the month prior to when the company plans its production. Since the company prepares the production plan for month *x* during month *x-1*, the forecast error from month *x-2* is considered for the upcoming production plan. This approach more accurately simulates real-world scenarios, where actual sales do not always align with the sales forecast.

The Simulated Inventory Position considering the Forecast Error in this case can be calculated according to (10).

$$\begin{aligned} &Simulated\ Inventory\ Position\ considering\ the\ Forecast\ Error_x \\ &\quad = Production\ Plan\ with\ Forecast\ Error_{x-L} \\ &\quad + \ Simulated\ Inventory\ Position_{x-1} - Actual\ Sales_x \end{aligned} \tag{10}$$

The Simulated Inventory Position, considering the forecast error, can then be compared with the actual inventory position of the company and with the simulated inventory positions derived from different methodologies. This comparison helps determine the most effective approach for the company. The production plan, target ending inventory position, and simulated inventory position considering the forecast error yielded by this methodology are displayed in Sections 4.1 and 4.2.

3.4.2 Production Plan Utilizing the Root Mean Squared Error of the Forecast (RMSE)

When utilizing the Root Mean Squared Error (RMSE) of the forecast, the primary distinction lies in the calculation of safety stock.

When a company relies on its forecasting process to predict future demand, instead of using historical data, the safety stock can be calculated according to (11).

$$Safety\ Stock_{x-1} = RMSE_{x-7\rightarrow x-1} * k * \sqrt{L+R} \tag{11}$$

Notation:

$RMSE_{x-7\rightarrow x-1}$ = Root Mean Squared Error of the forecast from time period *x-7* until time period *x-1* (units)

L = Replenishment Lead Time (time)

R = Review Period (units)

k = Safety Factor

The Root Mean Squared Error of the Forecast, is calculated according to (12) and (13).

$$Error\ Squared = \ (Actual\ Sales - Forecast\ Sales)^2 \tag{12}$$

$$RMSE = \ \textstyle\sum_{x-7}^{x-1} \frac{Error\ Squared}{6} \tag{13}$$

Notation:

$Error\ Squared$ = Forecast error squared for time period *x* (units)

RMSE = Root Mean Squared Error of the forecast (units)

n = Number of previous periods to be considered in the RMSE calculation (time)

Once a company defines the cycle service level, it is possible to calculate the safety factor that satisfies the condition above using tables or an Excel spreadsheet, according to (14).

$$k = NORMSINV\ (CSL) \tag{14}$$

The original production plan is calculated according to (15).

$$\begin{aligned} &Production\ Plan_{(x-1,\ x,\ x+L)} \\ &= Monthly\ Forecast_{x+L} + Safety\ Stock_{x-1} \\ &- Ending\ Inventory\ Position_{x+L\ -1} \end{aligned} \tag{15}$$

The Production Plan with forecast error and the Simulated Inventory Position considering the forecast error are calculated according to (9) and (10) respectively.

The production plan, target ending inventory position, and simulated inventory position considering the forecast error yielded by this methodology are displayed in Sections 4.1 and 4.2.

3.4.3 Production Plan Utilizing the Mean Squared Error Trending

Another production plan was simulated, employing the Mean Squared Error Trend methodology. In this approach, recent errors are weighted more heavily than older ones. Rather than assigning equal weight to the RMSE of the previous six months, more emphasis is placed on the most recent data. The omega parameter used was 0.05.

The production plan, target ending inventory position, and simulated inventory position considering the forecast error yielded by this methodology are displayed in Sections 4.1 and 4.2.

3.4.4 Production Plan Utilizing the Standard Deviation of the Forecast Error

The methodology for calculating the Production Plan using the Standard Deviation of the forecast error is similar to the RMSE methodology and its name is intuitive. Instead of calculating the safety stock using the RMSE of the forecast error, in this methodology it is calculated using the standard deviation of the forecast error. In this project, the Standard Deviation of the Forecast Error of the previous 6 months was used. Thus, the safety stock is calculated according to (16).

$$Safety\ Stock_{x-1} = Std.Dev.Fcst\ Error_{(x-6 \to x)} * k * \sqrt{L+R} \tag{16}$$

Once the safety stock is defined, the Production Plan considering the Forecast Error and the Simulated Inventory Position considering the forecast error are also determined by (7) and (8) respectively. The production plan, target ending inventory position, and simulated inventory position considering the forecast error yielded by this methodology are displayed in Sections 4.1 and 4.2.

3.4.5 Production Plan Through a Calculated DOI Target

This methodology combines the current approach utilized by the company with the Root Mean Squared Error methodology. In this method, we calculate the RMSE for the period between July 2021 and November 2023. The average RMSE for this entire period is used to determine the Safety Stock through equation (11). Then, we divide this calculated safety stock, which represents the average safety stock derived from the RMSE methodology from July 2021 to November 2023, by the average daily IMS for the same period to obtain the number of days that this safety stock represents. This process is repeated for all markets and products, and for each one, a production plan was also developed, considering the Days of Inventory (DOI) methodology.

The production plan, target ending inventory position, and simulated inventory position considering the forecast error yielded by this methodology are displayed in Sections 4.1 and 4.2.

3.5 Simulation Tool for Scenario Analysis

A Simulation Tool was developed to allow the company to analyze various future scenarios. This tool operates within a spreadsheet interface, allowing users to adjust variables such as the beginning and ending month, markets, products, service level, and the desired Days of Inventory (DOI) Target.

The simulation incorporates the reality that the volume produced in a specific month will be available in the market after lead time periods following the production. This lead time is adjusted based on a stochastic value following a Triangular Distribution. This distribution encompasses both the minimum lead time, indicating how early the volume might reach the market, and the maximum delay it could encounter. For example, with a lead time of 2 months or 60 days, considering a Lead Time Anticipation at 10% and Lead Time Delay at 30%, the volume could reach the market anywhere between 54 days (10% earlier) and 78 days (30% delayed). The Triangular Distribution, unlike a uniform distribution, suggests that the probability of volume arrival is not evenly spread across its range. It is more likely for the volume to arrive closer to the mode, which in this example, is at 60 days. This mode represents the most probable arrival point, indicating that occurrences near the midpoint are more frequent than those at the extremes. The Triangular Distribution was chosen because it accurately reflects the complexities encountered in operations. Consequently, when there's a delay, the number of days tends to be greater than in the case of an advance. Therefore, in this scenario, we consider that if the lead time is 60 days, the product may advance by 6 days (10%), but it could also be delayed by 18 days (30%).

The same principle applies when deriving Simulated Sales. Utilizing the Sales Forecast as input, the triangular distribution factors in both a Forecast Error Min and a Forecast Error Max. For instance, if the forecast predicts 120,000 units, the range of Simulated Sales will span from 84,000 units to 132,000 units.

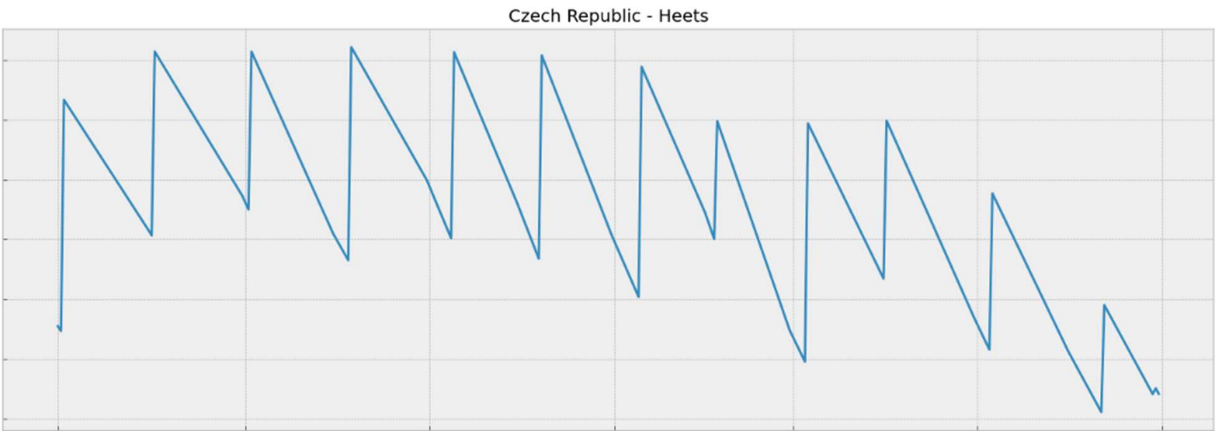
In the Simulation Tool, the company has the flexibility to adjust the inputs showed in Figure E-1 for conducting scenario analysis. Each modification produces a distinct scenario, enabling the company to make comprehensive analysis of the trade-offs inherent in different scenarios.

After defining the parameters, the company enters the forecast values for the upcoming months, along with the actual inventory position from the previous month, and the already established production plans that will be available in the market in the following months, thus impacting the inventory position for the subsequent periods. These inputs are necessary for initializing the simulation model, which follows the methodology of Days of Inventory outlined in Section 3.4.1.

The simulation run in Python generates both a chart and a data frame with the inventory position, which can then be exported to Excel for additional scenario analysis.

Figure 3-8

Simulated Daily Inventory Position for Scenario Analysis



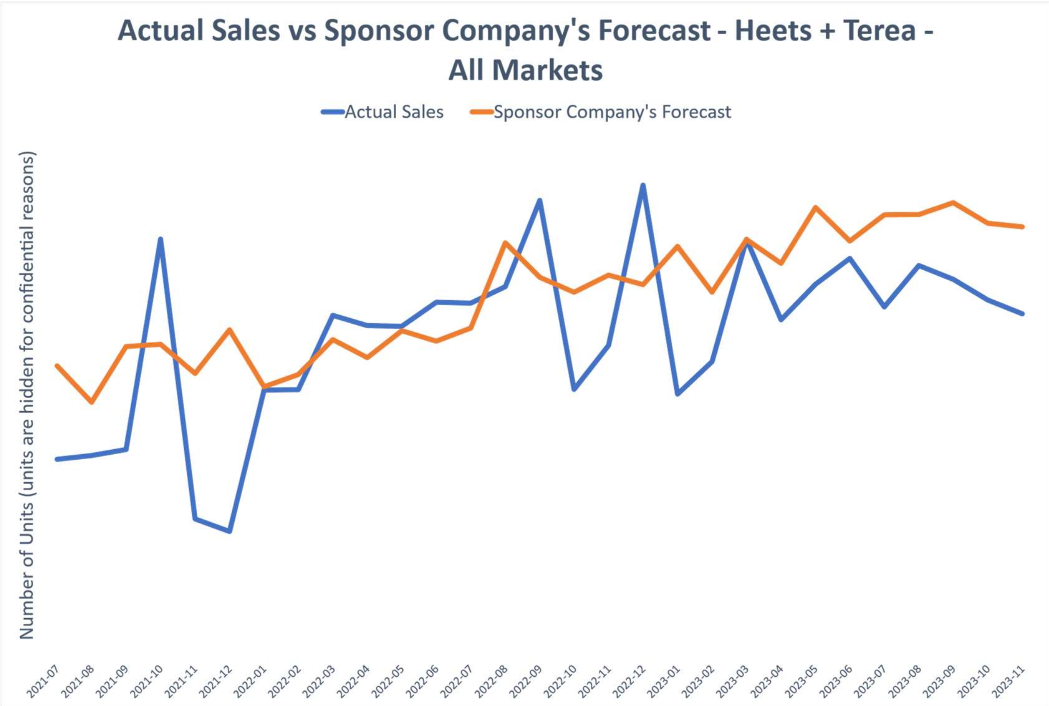
4. Results

4.1 Comparing Different Forecast Techniques with the Sponsor Company's Forecasting

To analyze the forecasting process of the sponsor company, we aggregated the Actual Sales of the two products and four markets under the scope of the project to compare with their respective forecasts. In Figure 4-1, we can observe the behavior of the two lines, showing that Actual Sales most of the time fall below the forecast. It is also noticeable that sales demonstrated an increasing trend from July 2021 to December 2022, and during the year 2023, sales stabilized.

Figure 4-1

Actual Sales vs the Sponsor Company's forecast – Heets+Terea – All Markets



From July 2021 to November 2023, the accumulated MAPE of the sponsor company's Sales Forecast was 28%, which can be observed in Table B-1 in Appendix B.

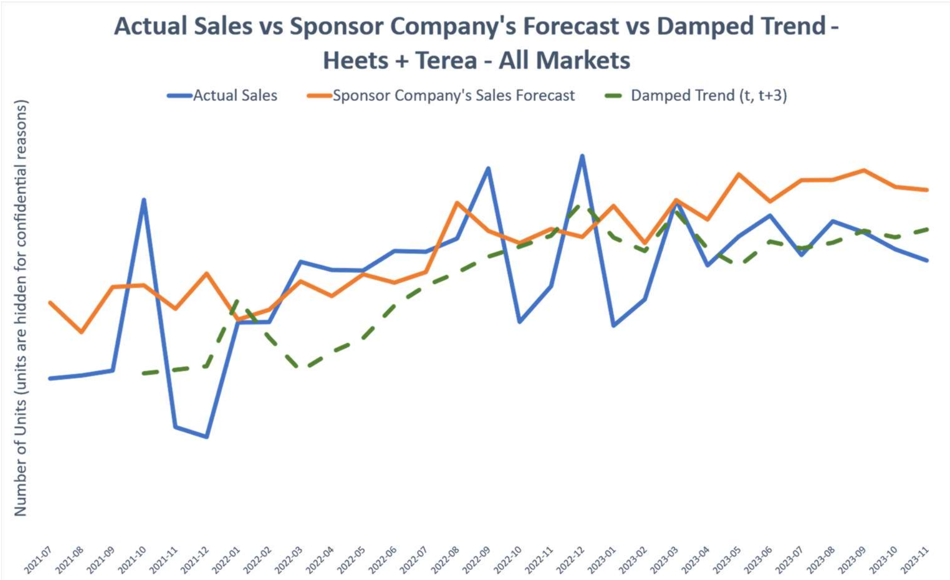
In Section 4.1 we concentrated on evaluating Exponential Smoothing with Damped Trend against the company's forecast, highlighting its accuracy in mirroring the actual business scenario. Detailed comparisons of this method with other forecasting techniques used by the company are documented in Appendix B.

4.1.1 Exponential Smoothing with Damped Trend vs the Sponsor Company's Forecast-Forecasting for *t+3* in Time Period *t*

Considering the company's reality of forecasting three months ahead, the Exponential Smoothing with Damped Trend methodology exhibited a cumulative MAPE of 20.7%, compared to the company's current forecast MAPE of 28%.

Figure 4-2

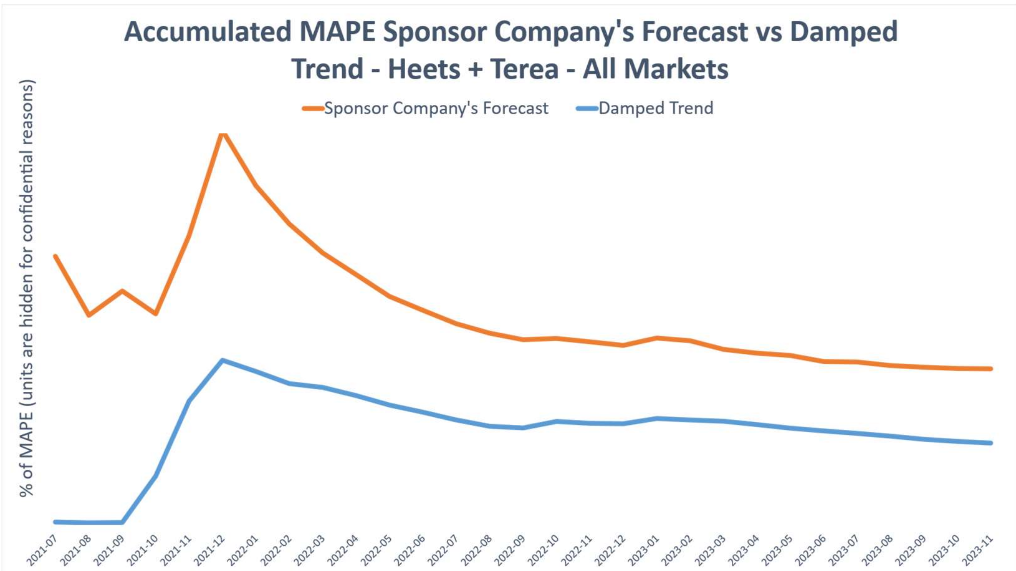
Actual Sales vs the Sponsor Company's Forecast vs Damped Trend – Heets + Terea – All Markets



In Figure 4-3, we can observe that the Damped Trend model consistently had a MAPE lower than the MAPE of the company's forecast.

Figure 4-3

Sponsor Company's Forecast vs Damped Trend – Heets + Terea – All Markets



By analyzing Table 4-1, we can conclude that if the company had utilized the Damped Forecasting technique instead of its current process, its inventory position would have been, on average, 0.7% lower throughout the year.

Table 4-1

Inventory Reduction of 0.7% Comparing the Damped Trend Forecasting Technique With the Company's Forecasting Process Considering the Calculated DOI Methodology

ALL PRODUCTS AND MARKETS - SPONSOR COMPANY'S FORECAST & LEADTIME = 3 MONTHS						
Production Plan Methodology	Cycle Stock (Units)	Inventory Target = Calculated Safety Stock (Units)	Inventory Position Considering Forecast Error (Units)	Additional Inventory Due to Forecast Error (%)	In Transit Inventory (Units)	Total End to End Inventory (Units)
STD DOI Target	436,216	2,189,598	2,260,887	3.3%	2,398,669	5,095,771
Calculated DOI	436,216	801,301	924,169	15.3%	2,305,976	3,666,361
RMSE	436,216	766,835	861,692	12.4%	2,378,869	3,676,777
Std Dev. Forecast Error	436,216	751,604	854,840	13.7%	2,348,612	3,639,668
MSE Trending	436,216	845,572	949,010	12.2%	2,405,642	3,790,868

ALL PRODUCTS AND MARKETS - DAMPED TREND FORECAST & LEADTIME							
Production Plan Methodology	Cycle Stock (Units)	Inventory Target = Calculated Safety Stock (Units)	Inventory Position Considering Forecast Error (Units)	Additional Inventory Due to Forecast Error (%)	In Transit Inventory (Units)	Total End to End Inventory (Units)	Inventory Reduction Company's Forecast vs Damped Trend Forecasting (%)
STD DOI Target	436,216	2,031,301	2,038,281	0.3%	2,338,243	4,812,740	-5.6%
Calculated DOI	436,216	892,820	897,569	0.5%	2,306,115	3,639,899	-0.7%
RMSE	436,216	879,112	890,025	1.2%	2,345,484	3,671,724	-0.1%
Std Dev. Forecast Error	436,216	829,185	840,098	1.3%	2,349,229	3,625,544	-0.4%
MSE Trending	436,216	942,949	953,182	1.1%	2,400,907	3,790,305	0.0%

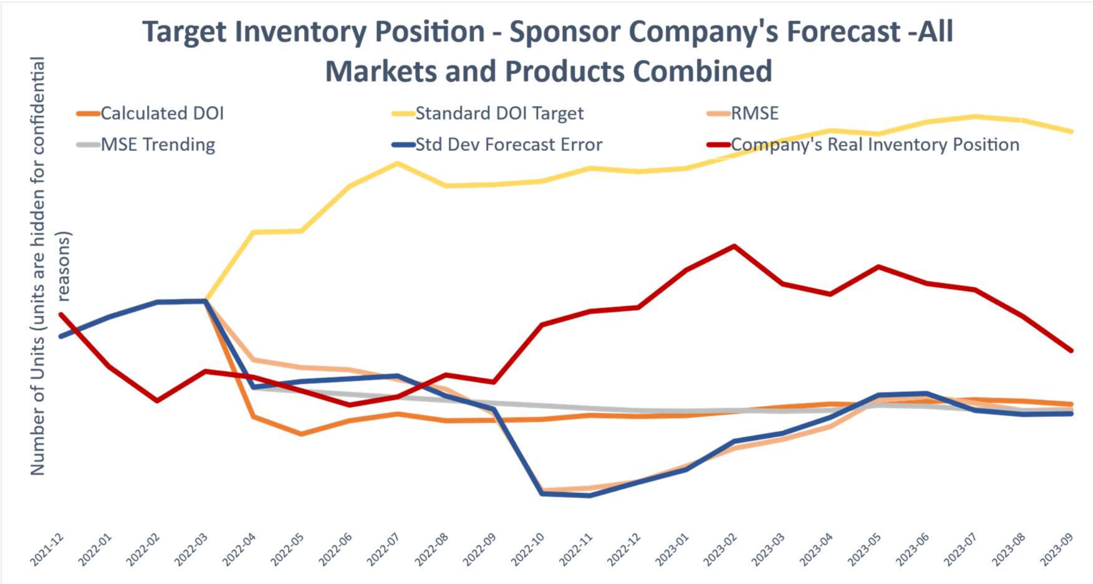
**The figures in the tables above have been altered to ensure confidentiality.*

4.2 Inventory Position Tradeoff Among Different Production Plans

Figure 4-4 shows the target ending inventory position of different production plans. As previously explained in this project, the production plans are calculated considering that the market will sell according to the sales forecast, since every production plan is planned for the future. When the forecast error is not considered in the models, the ending inventory position will equal the safety stock calculated for that specific month. These values represent the quantity of units the company aims to have by the end of each month.

Figure 4-4

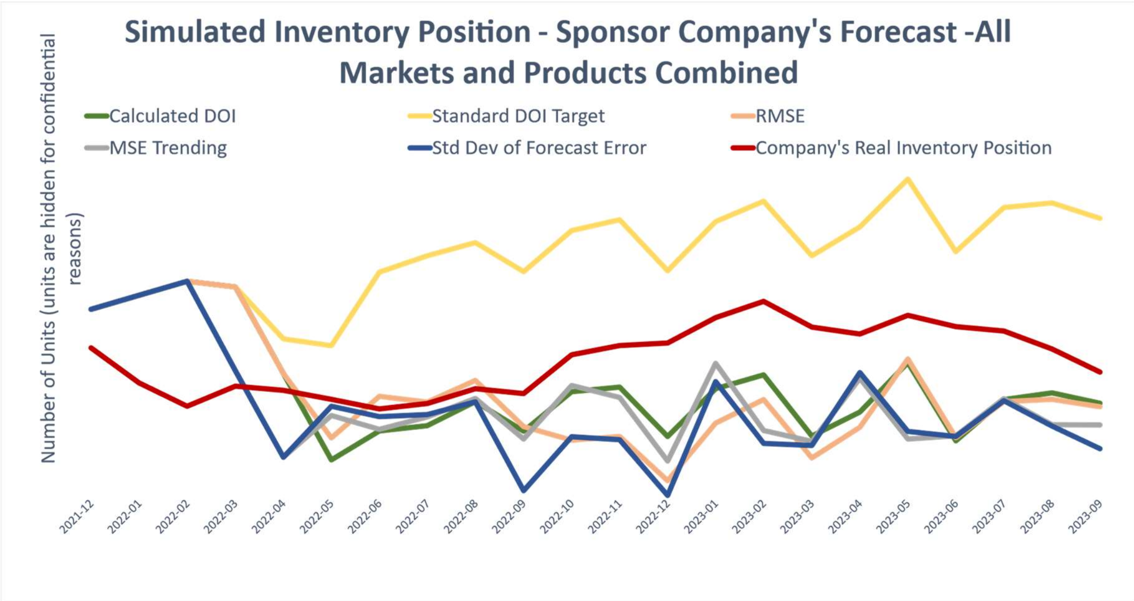
Target Inventory Position – The Sponsor Company's Forecast – All Markets and Products



In this scenario, we could compare how the target ending inventory position for each month changes in response to the changes in different production plans, but we cannot compare these curves with the real stock position of the company because the company's real stock position was influenced by the forecast error. Therefore, to compare different production plans among themselves and compare them with the real stock position of the company, the forecast error should be considered in the model. Figure 4-5 displays the inventory position at the end of each month after considering the forecast error.

Figure 4-5

Simulated Inventory Position – the Sponsor Company's Forecast – All markets and Products



The curves reveal that all models are currently affected by the forecast error, closely reflecting the pattern observed in the Real Stock Position curve. Notably, the model with a Standard DOI, consistently maintains higher inventory levels than others and exceeds the company's stock levels in the market. Both the MSE Trending and the Calculated DOI methodology exhibit similar performances. In contrast, the RMSE and Standard Deviation of the Forecast Error methodology, when aggregated presented an inventory position close to zero in one specific month, suggesting potential stockout events upon disaggregation across one or more markets and products.

The inventory metrics of the five different production plans can be observed in Table 4-2. By analyzing the numbers and the graphic of the simulated inventory position, we can see that the Standard DOI inventory target is clearly excessive, leaving the company with excess inventory in the market, which increases its inventory cost as well as the risk of Loss of Good Sold (LOGD).

Table 4-2

The Sponsor Company's Forecast & Leadtime = 3 months

ALL PRODUCTS AND MARKETS - SPONSOR COMPANY'S FORECAST & LEADTIME = 3							
Production Plan Methodology	**Cycle Stock (Units)**	**Inventory Target = Calculated Safety Stock (Units)**	**Inventory Position Considering Forecast Error (Units)**	**Additional Inventory Due to Forecast Error (%)**	**In Transit Inventory (Units)**	**Total End to End Inventory (Units)**	**Inventory Cost Reduction Production Plan Methodology vs the Company's**
STD DOI Target	436,216	2,189,598	2,260,887	3.3%	2,398,669	5,095,771	+19%
Calculated DOI	436,216	801,301	924,169	15.3%	2,305,976	3,666,361	-14%
RMSE	436,216	766,835	861,692	12.4%	2,378,869	3,676,777	-14%
Std Dev. Forecast Error	436,216	751,604	854,840	13.7%	2,348,612	3,639,668	-15%
MSE Trending	436,216	845,572	949,010	12.2%	2,405,642	3,790,868	-11%
Company's Inventory Position	436,216	N/A	1,213,684	N/A	2,617,294	4,267,194	Baseline

**The figures in the table above have been altered to ensure confidentiality.*

The Standard Deviation of the Forecast Error methodology exhibited the lowest inventory levels in the market. However, as mentioned earlier, this metric also resulted in stockout events.

The RMSE metric, in addition to experiencing stockout events, showed high inventory metrics, indicating inefficiency in stock calibration. At times, the inventory was insufficient, while at other times, it exceeded the necessary levels.

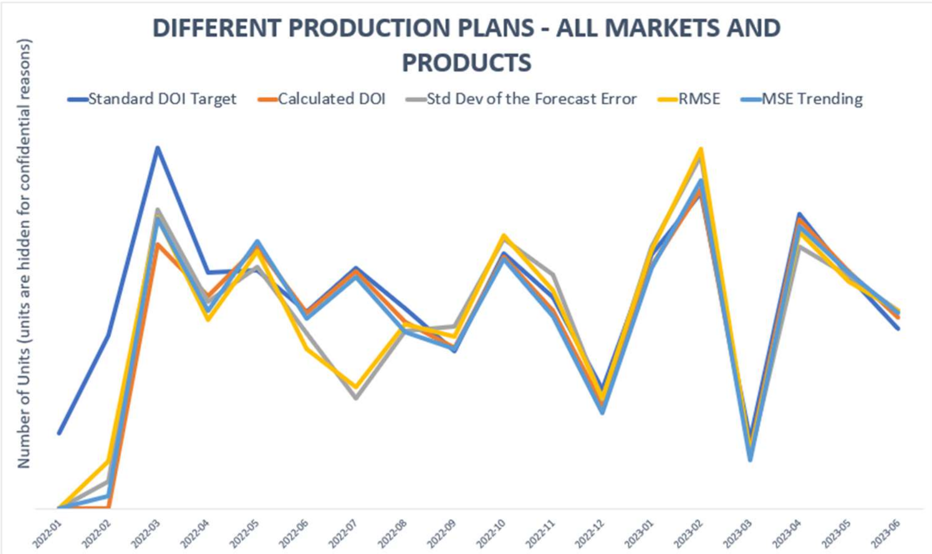
Both the RMSE Trending methodology and the Calculated DOI, which was 21 days in the aggregated position, presented very similar metrics without encountering stockout events.

4.3 Production Plan Analysis Comparing Different Methodologies

Analyzing the various production plan curves reveals a tendency for the models to converge over time. The primary discrepancies occur in the initial months, where production plans with higher safety stocks initially have greater output. Thus, the variance among the different inventory calculation methodologies has a more pronounced impact on the volumes to be produced by the factories in the early months. Over time, the influence of different production plan methodologies becomes more significant on the inventory remaining in the market rather than on the volume to be produced by the facilities as displayed in Figure 4-1.

Figure 4-6

Different Production Plans – All Markets and Products



4.4 Analyzing the Impact of Lead Time Reduction on Inventory Position

In Table 4-3, the impact of a higher lead time on the company's inventory position can be observed. By reducing the lead time from 3 months to 2 months, inventory is significantly lowered, by 21.3%.

Table 4-3

Inventory Reduction of 21.3% for a lead time of 2 Months Versus 3 Months on the Calculated DOI

ALL PRODUCTS AND MARKETS - SPONSOR COMPANY'S FORECAST & LEADTIME = 3 MONTHS						
Production Plan Methodology	Cycle Stock (Units)	Inventory Target = Calculated Safety Stock (Units)	Inventory Position Considering Forecast Error (Units)	Additional Inventory Due to Forecast Error (%)	In Transit Inventory (Units)	Total End to End Inventory (Units)
STD DOI Target	436,216	2,189,598	2,260,887	3.3%	2,398,669	5,095,771
Calculated DOI	436,216	801,301	924,169	15.3%	2,305,976	3,666,361
RMSE	436,216	766,835	861,692	12.4%	2,378,869	3,676,777
Std Dev. Forecast Error	436,216	751,604	854,840	13.7%	2,348,612	3,639,668
MSE Trending	436,216	845,572	949,010	12.2%	2,405,642	3,790,868

ALL PRODUCTS AND MARKETS - SPONSOR COMPANY'S FORECAST & LEADTIME = 2 MONTHS							
Production Plan Methodology	Cycle Stock (Units)	Inventory Target = Calculated Safety Stock	Inventory Position Considering Forecast Error	Additional Inventory Due to Forecast Error (%)	In Transit Inventory (Units)	Total End to End Inventory (Units)	Inventory Reduction Decreasing 1 Month of Leadtime (%)
STD DOI Target	436,216	2,208,516	2,244,144	1.6%	1,670,446	4,350,805	-14.6%
Calculated DOI	436,216	757,647	852,446	12.5%	1,595,547	2,884,209	-21.3%
RMSE	436,216	729,575	789,160	8.2%	1,641,711	2,867,087	-22.0%
Std Dev. Forecast Error	436,216	704,266	772,231	9.7%	1,623,175	2,831,622	-22.2%
MSE Trending	436,216	810,746	880,727	8.6%	1,660,931	2,977,874	-21.4%

**The figures in the tables above have been altered to ensure confidentiality.*

5. Discussion

5.1. Insights and Recommendations After Comparing Different Forecast Techniques With the Sponsor Company's Forecast

Comparing the MAPE of the sponsor company's Forecast (28%) with the MAPE of the Exponential Smoothing with Damped Trend (20.7%), forecasting in time *t* for time period *t+3*, we observed that the latter methodology presented better results in terms of MAPE. This indicates that the mathematical model was more accurate than the company's current process, which combines market expert information, planning team input, and financial guidelines, among others. The Exponential Smoothing with Damped Trend yielded superior results because the company's forecast exhibits a noticeable bias.

The accuracy of the company's current forecast needs improvement. To achieve this, it is necessary to review the process to identify areas that need correction, since the current forecast inaccuracy is resulting in excessive inventory in the market, leading to additional costs and risks for the company. Thus, it is imperative to enhance the existing forecasting process to mitigate these challenges. Additionally, the company should ensure that its forecast is more accurate than the mathematical model, which leverages the expertise of its market experts.

Therefore, we recommend that the company continue with its subjective forecasting process, which involves alignment among various departments. However, it is crucial to review this process in search of enhancements and bias reduction. Additionally, the company should consistently compare its forecasting metric results against the objective method provided by the Exponential Smoothing with Damped Trend model. It is important to note that if the company's forecasting process results in a higher MAPE (Mean Absolute Percentage Error) than the objective model, it will significantly affect its inventory position, leading to higher inventory costs.

5.2. Production Plan Insights and Recommendations after Comparing Different Safety Stock Methodologies

The Calculated DOI methodology for the aggregate position was 21 days. However, since this metric is being evaluated for the entire period from July 2021 to November 2023 and sales values for Terea markets only started to be available from November 2022, the model does not consider forecast errors for Terea for a long period, which consequently lowers the RMSE in the aggregate position. The best way to define a Calculated DOI that is closer to an optimized position but does not expose the company to unnecessary stockout risks is by analyzing the Calculated DOI across the four Heets markets, which are more mature.

Applying the Calculated DOI methodology to Heets for the four markets under the scope of our analysis, we found the Calculated DOI values shown in Table 5-1.

Table 5-1

Calculated Days of Inventory per Market

Market	Calculated DOI (Days of Inventory)
Czech Republic	26
Hungary	34
Slovak Republic	25
Poland	28

Appendix C displays the inventory position of all four markets based on the five different production plans assessed by this project.

Taking into consideration the figures in Table 5-1 and analyzing all the simulated inventory curves market by market to identify any instances of stockout events, as well as examining the inventory metrics presented in Table 4-2, we observed that the technique referred to as Standard Days of Inventory (DOI) Target exhibited higher inventory metrics, indicating a result 19% worse than what the company achieved during the same period. The methods labeled as Calculated DOI, Root Mean Square Error (RMSE), and Standard Deviation of Forecast Error demonstrated very similar metrics, yielding an inventory position of 14%, 15%, and 14% lower than the company's inventory position for the respective period. However, the RMSE and Standard Deviation of Forecast Error methodologies were on the verge of experiencing a stockout event in December 2022 in the aggregate position, encompassing all products and markets. This suggests the likelihood of a stockout event occurring in some market during that month.

Therefore, our recommendation is for the company to adopt a Calculated DOI of 40 days for all markets for both products. This approach would ensure that the company maintains a buffer inventory of 40 days at the end of each month to mitigate against shipment delays or actual sales that exceed forecasts.

6. Conclusion

This project simulates the goal-seeking behavior of a dynamic supply chain using System Dynamics, exploring how equilibrium is pursued through inventory policies. It then adapts the sponsor company's data and conducts a detailed examination of various inventory policies and their distinct impacts. The dynamic and analytical simulations were effective and can be further expanded and integrated.

We used simulation to understand the impact of various forecasting techniques and safety stock methodologies on the company's production plans and simulated inventory positions, leading to several conclusions.

Firstly, in the aggregate position, which tends to decrease the forecast error, the accumulated MAPE of the company's forecast was 28%. The Accumulated MPE in the same period was -21%, also showing that the company's forecasting process exhibits a high bias, as the Actual Sales consistently fall below the target. Forecast inaccuracies have led to overstocks across multiple markets, leading to higher inventory costs and higher risks of LOGD costs, and highlighting the importance of refining forecasting models and processes to better align with actual sales trends. While objective forecasting models like Exponential Smoothing with Damped Trend presented a lower Accumulated MAPE of 20.7%, this forecasting technique should serve as a useful guide to complement, rather than replace the subjective forecasting process that relies on the expertise of market experts within the company.

Secondly, this work developed the method denominated as Calculated DOI, adapting the RMSE methodology to the current process employed by the sponsor company, seeking to identify the ideal methodology for the company to work with. By setting the DOI to 40 days across all markets and products, the company can establish a buffer inventory that buffers against shipment delays and unexpected increases in sales. This balanced approach has proven to maintain sufficient inventory levels without unnecessarily exposing the company to risks during this policy change. A simulation tool, incorporating the recommended methodology, has been provided to the company, which could serve as a valuable tool for conducting scenario analysis in the future.

Third, it was also evident how impactful an increase in lead time is on the company's inventory position. A one-month reduction in lead time resulted in a 21.3% decrease in inventory position for the company when considering cycle stock, safety stock, and in-transit inventory, underscoring the importance of the company seeking ways to reduce lead time.

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Appendix A – Diffusion Model Analysis

Figure A-1

Fitting the Logistic Model to Data for Hungary for HnB Adoption Over Addressable Population

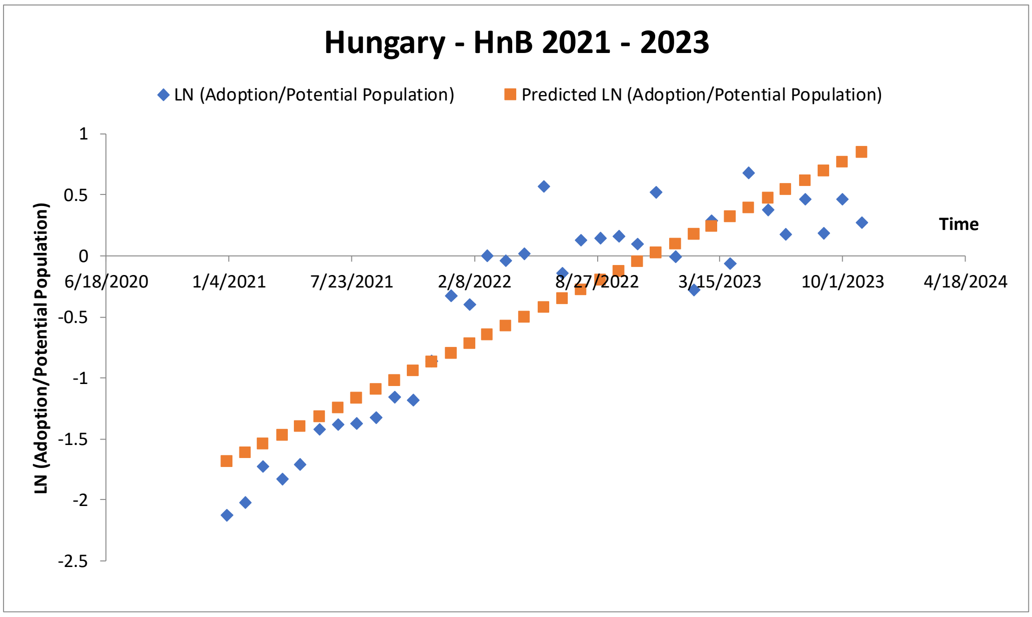


Figure A-2

Fitting the Logistic Growth (1) to data for Poland for HnB adoption over addressable population.

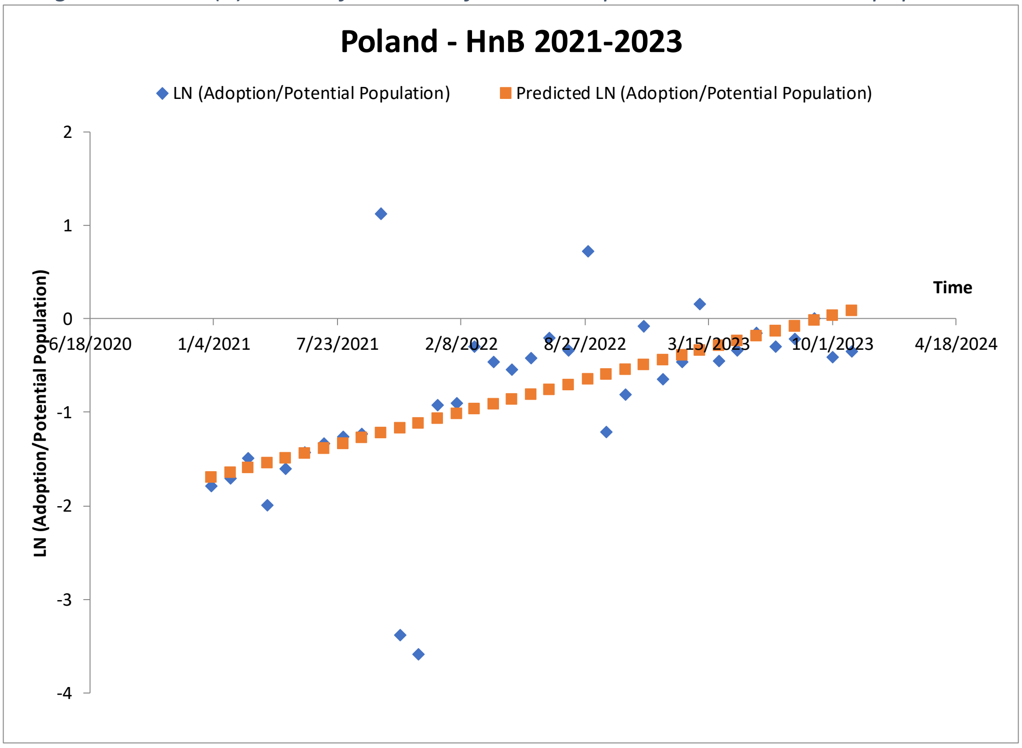


Table A-1

Fitting the Logistic Growth (1) model to data for Hungary for HnB adoption over addressable population regression results of Figure A-1

R Square	*Adjusted R Square*	*Coefficients (intercept)*	*Coefficients (Time)*
0.796327534	*0.79*	*-109.93****	*0.0025****

Table A-2

Fitting the Logistic Growth (1) to data for Poland for HnB adoption over addressable population regression results of Figure A-2

R Square	*Adjusted R Square*	*Coefficients (intercept)*	*Coefficients (Time)*
0.31	*0.29*	*-77.72****	*0.0017****

Figure A-3

Fitting to data for Slovak Republic for HnB adoption over addressable population.

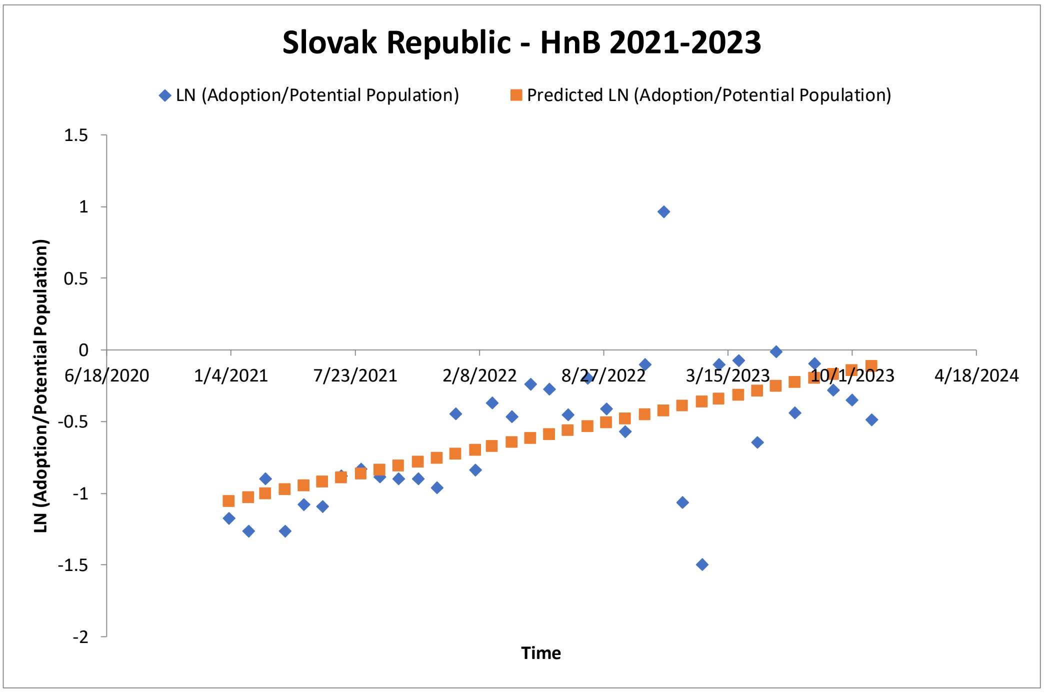


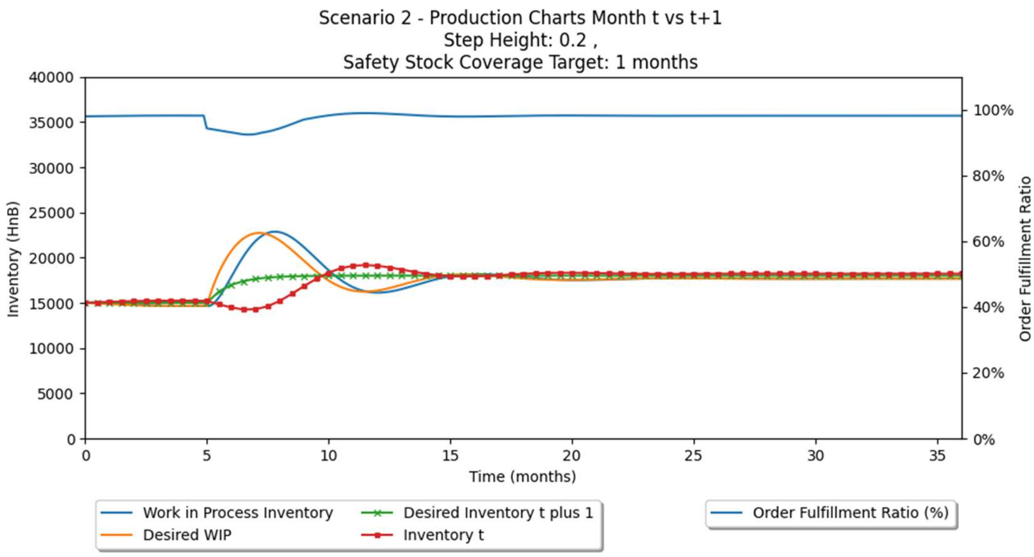
Table A-3

Fitting the Logistic Growth model to data for Slovak Republic for HnB adoption over addressable population regression results of Figure A-3

R Square	*Adjusted R Square*	*Coefficients (intercept)*	*Coefficients (Time)*
0.345125027	*0.33*	*-41.29****	*0.0009****

Table A-4

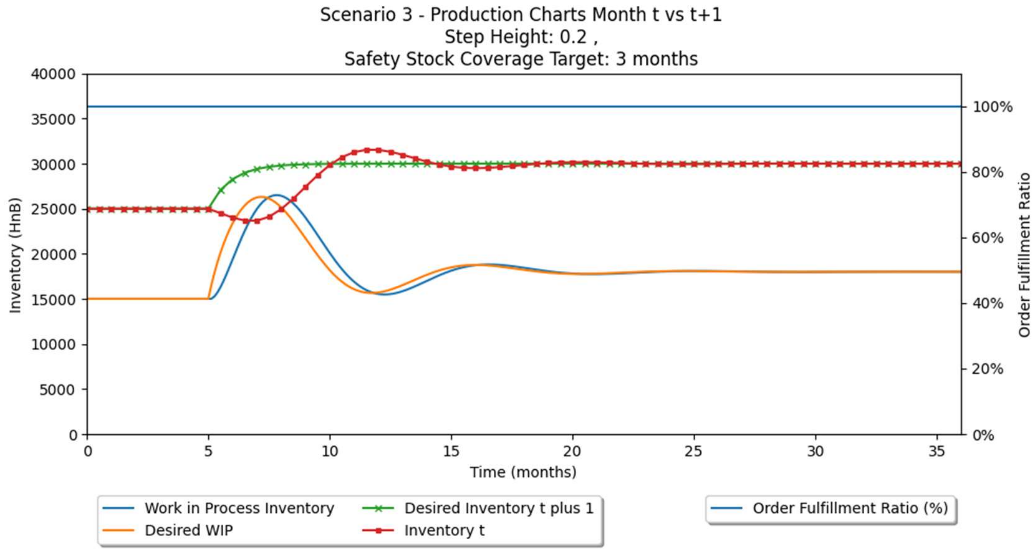
System dynamic simulation of a step increase of 20%,



Notes. Safety Stock at ½ default, service level below 100% during the initial months.

Table A-5

System dynamic simulation of a step increase of 20%,



Notes. inventory cycle time increased to 1.5x default.

Table A-6

System Dynamic Simulation of a Step Increase of 20%.

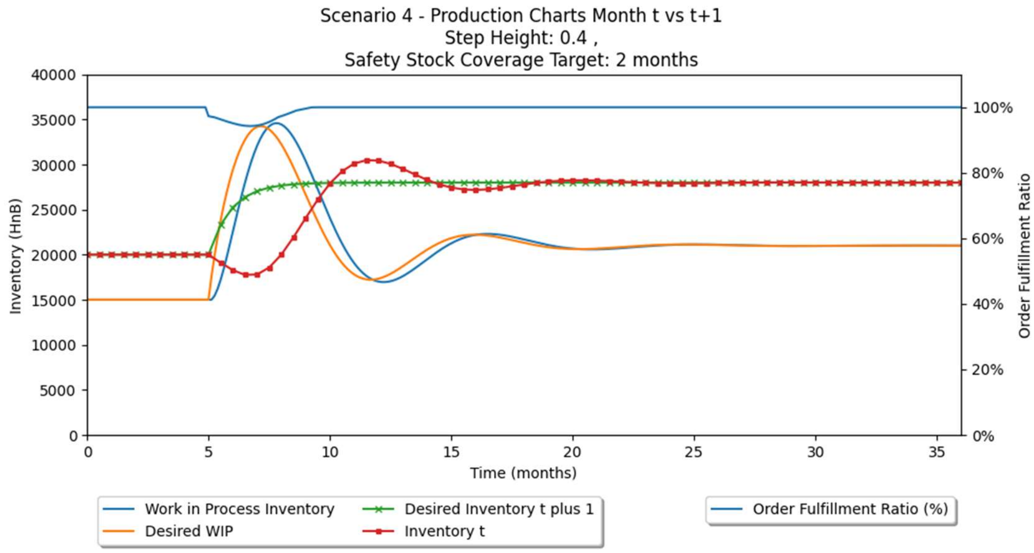


Table A-7

System dynamic simulation of inventory levels of Manufacturing Lead Time 2x Default and a Step Increase of 20%

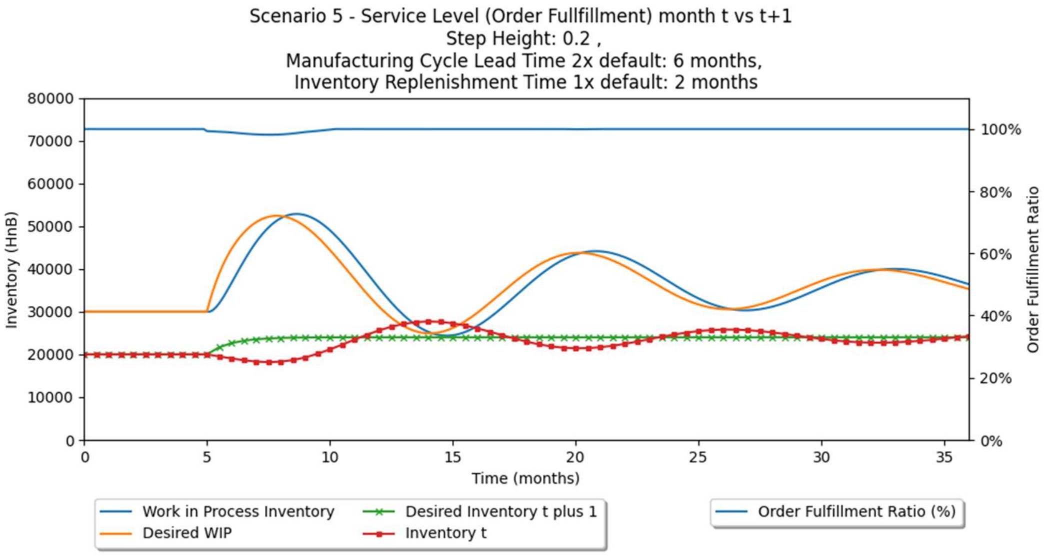
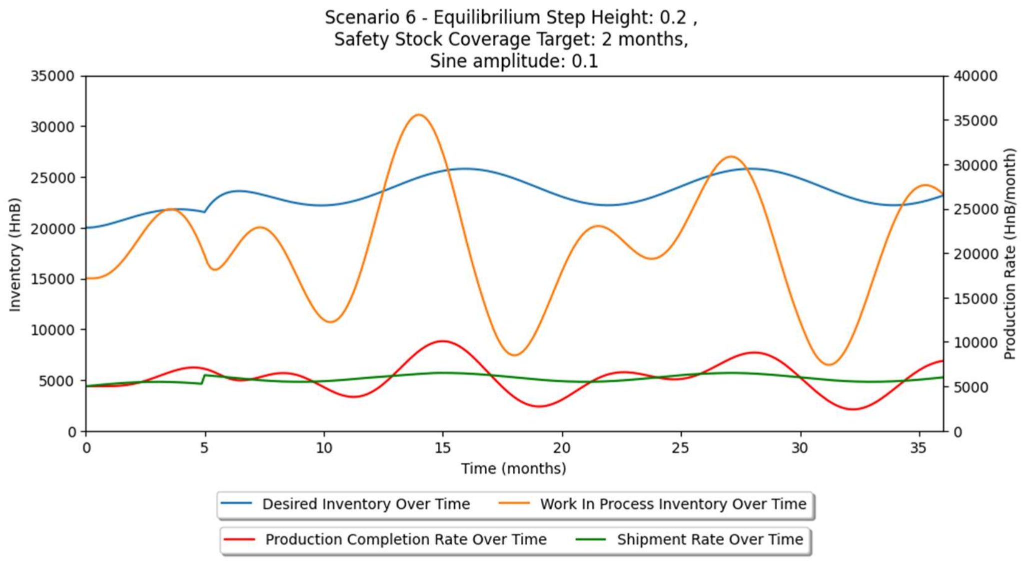


Table A-8

System Dynamic Simulation of Inventory at a Step Increase 20% in Sine Amplitude pattern.



Appendix B – Forecasting Analysis

B.1 - Company's Forecasting Analysis

Table B-1 illustrates that the company´s forecast presented an Accumulated MAPE of 28%.

Table B-1

Sponsor Company´s forecast metrics

Date	Montlhy MAPE PMI Forecast	Accumulated MAPE PMI Forecast
2021-07	48%	48%
2021-08	27%	28%
2021-09	50%	29%
2021-10	25%	29%
2021-11	108%	31%
2021-12	165%	35%
2022-01	1%	34%
2022-02	6%	33%
2022-03	7%	33%
2022-04	10%	32%
2022-05	1%	31%
2022-06	11%	31%
2022-07	7%	30%
2022-08	12%	30%
2022-09	17%	30%
2022-10	37%	30%
2022-11	23%	30%
2022-12	21%	29%
2023-01	57%	30%
2023-02	24%	30%
2023-03	0%	29%
2023-04	17%	29%
2023-05	21%	29%
2023-06	4%	28%
2023-07	27%	28%
2023-08	13%	28%
2023-09	20%	28%
2023-10	22%	28%
2023-11	26%	28%

B.2 Moving Average – Forecasting for t+1 in Time Period t

A Moving Average Forecast of 3 months and 6 months was assessed in each market and product to compare with the company's current forecasting process.

Comparing the 3-month Moving Average with the 6-month Moving Average and the sponsor Company Sales Forecast, we can observe that both Moving Averages exhibited better metrics. Specifically, the 3-month Moving Average showed an Accumulated MAPE of 23.2%, while the 6-month Moving Average presented an Accumulated MAPE of 18.2%, whereas the Accumulated MAPE of the Sponsor Company was 28%, as discussed earlier.

Table B-2

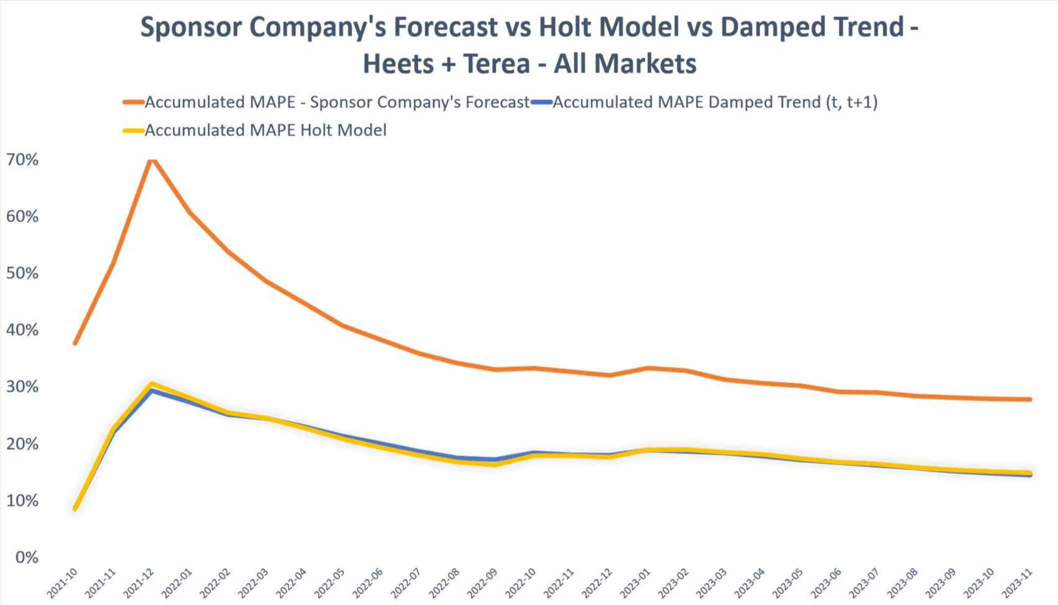
Moving Average – Forecasting for t+1 in Time Period t

Date	Montlhy MAPE PMI Forecast	Accumulated MAPE PMI Forecast	Monthly MAPE M3 Forecast	Accumulated MAPE M3 Forecast	Monthly MAPE M6 Forecast	Accumulated MAPE M6 Forecast
2021-07	48%	48%				
2021-08	27%	28%				
2021-09	50%	29%				
2021-10	25%	29%	52.0%	52.0%		
2021-11	108%	31%	102.1%	27.0%		
2021-12	165%	35%	105.4%	29.7%		
2022-01	1%	34%	15.0%	29.2%	24.6%	24.6%
2022-02	6%	33%	34.3%	29.4%	18.5%	18.4%
2022-03	7%	33%	36.0%	29.6%	44.6%	19.4%
2022-04	10%	32%	12.1%	29.1%	28.1%	19.8%
2022-05	1%	31%	5.3%	28.4%	35.4%	20.3%
2022-06	11%	31%	5.8%	27.7%	28.3%	20.6%
2022-07	7%	30%	4.2%	27.1%	12.3%	20.3%
2022-08	12%	30%	6.5%	26.5%	12.3%	20.1%
2022-09	17%	30%	21.4%	26.4%	31.8%	20.4%
2022-10	37%	30%	47.7%	26.9%	27.2%	20.6%
2022-11	23%	30%	17.3%	26.7%	12.5%	20.4%
2022-12	21%	29%	27.0%	26.7%	34.2%	20.8%
2023-01	57%	30%	33.7%	26.8%	29.6%	21.0%
2023-02	24%	30%	18.3%	26.6%	17.4%	20.9%
2023-03	0%	29%	17.9%	26.5%	21.5%	20.9%
2023-04	17%	29%	3.6%	25.9%	0.2%	20.4%
2023-05	21%	29%	6.1%	25.5%	6.8%	20.1%
2023-06	4%	28%	5.7%	25.1%	10.9%	19.8%
2023-07	27%	28%	5.6%	24.7%	0.8%	19.4%
2023-08	13%	28%	4.6%	24.3%	8.2%	19.1%
2023-09	20%	28%	0.6%	23.8%	0.1%	18.7%
2023-10	22%	28%	4.6%	23.4%	3.9%	18.4%
2023-11	26%	28%	9.5%	23.2%	8.5%	18.2%

Figure B-1 illustrates that the Moving Average of 6 months is the one with the lowest MAPE.

Figure B-1

Accumulated MAPE the Sponsor Company's Forecast vs Holt Model vs Damped Trend – Heets + Terea – All Markets



B.3 Exponential Smoothing Holt Model Forecast – Forecasting for *t+1* in Time Period *t*

The Holt Model presented an Accumulated MAPE of 14.9%, compared to 28% of the sponsor company, as can be observed in Table B-4.

Table B-4

Exponential Smoothing Holt Model forecast – forecasting for t+1 in Time period t

Date	Montlhy MAPE PMI Forecast	Accumulated MAPE PMI Forecast	Monthly MAPE Holt Model	Accumulated MAPE Holt Model
2021-07	48%	48%	0.2%	0.2%
2021-08	27%	28%	0.6%	14.0%
2021-09	50%	29%	0.5%	13.6%
2021-10	25%	29%	32.8%	14.1%
2021-11	108%	31%	79.2%	16.1%
2021-12	165%	35%	70.4%	17.6%
2022-01	1%	34%	13.0%	17.5%
2022-02	6%	33%	7.2%	17.2%
2022-03	7%	33%	16.9%	17.2%
2022-04	10%	32%	7.1%	16.9%
2022-05	1%	31%	1.7%	16.6%
2022-06	11%	31%	2.8%	16.2%
2022-07	7%	30%	1.5%	15.9%
2022-08	12%	30%	1.1%	15.5%
2022-09	17%	30%	9.6%	15.4%
2022-10	37%	30%	42.3%	16.0%
2022-11	23%	30%	17.9%	16.0%
2022-12	21%	29%	13.4%	16.0%
2023-01	57%	30%	42.0%	16.5%
2023-02	24%	30%	19.8%	16.6%
2023-03	0%	29%	9.4%	16.4%
2023-04	17%	29%	10.2%	16.3%
2023-05	21%	29%	1.0%	16.0%
2023-06	4%	28%	2.4%	15.8%
2023-07	27%	28%	9.1%	15.6%
2023-08	13%	28%	0.5%	15.4%
2023-09	20%	28%	3.4%	15.2%
2023-10	22%	28%	7.6%	15.0%
2023-11	26%	28%	9.0%	14.9%

B.4 Exponential Smoothing Damped Trend Forecast – Forecasting for *t+1* in Time Period *t*

Table B-5 displays the execution of the Exponential Smoothing – Damped Trend Forecast. This model presented an Accumulated MAPE of 14.5%, compared to 28.0% of the company's forecast.

Table B-5

Exponential Smoothing – Damped Trend Forecast – Forecasting for t+1 in Time Period t.

Date	Montlhy MAPE PMI Forecast	Accumulated MAPE PMI Forecast	Monthly MAPE Damped Trend	Accumulated MAPE Damped Trend
2021-07	48%	48%	0.4%	0.4%
2021-08	27%	28%	0.1%	13.6%
2021-09	50%	29%	0.4%	13.2%
2021-10	25%	29%	33.6%	13.8%
2021-11	108%	31%	75.8%	15.6%
2021-12	165%	35%	66.0%	17.1%
2022-01	1%	34%	15.3%	17.0%
2022-02	6%	33%	9.7%	16.8%
2022-03	7%	33%	19.1%	16.9%
2022-04	10%	32%	9.7%	16.7%
2022-05	1%	31%	4.7%	16.4%
2022-06	11%	31%	5.9%	16.2%
2022-07	7%	30%	2.0%	15.8%
2022-08	12%	30%	2.7%	15.5%
2022-09	17%	30%	12.9%	15.4%
2022-10	37%	30%	36.1%	15.9%
2022-11	23%	30%	12.5%	15.8%
2022-12	21%	29%	17.0%	15.9%
2023-01	57%	30%	35.4%	16.3%
2023-02	24%	30%	14.1%	16.2%
2023-03	0%	29%	13.2%	16.2%
2023-04	17%	29%	5.7%	16.0%
2023-05	21%	29%	2.8%	15.7%
2023-06	4%	28%	5.8%	15.5%
2023-07	27%	28%	5.5%	15.3%
2023-08	13%	28%	3.6%	15.1%
2023-09	20%	28%	0.4%	14.9%
2023-10	22%	28%	4.7%	14.7%
2023-11	26%	28%	6.2%	14.5%

Figure B-2 displays the curve of the Accumulated MPE for the three different forecast approaches. We can observe that the Damped Trend is the closest to 0.

Figure B-2

Accumulated MAPE the Sponsor Company's Forecast vs Holt Model vs Damped Trend – Heets + Terea – All Markets

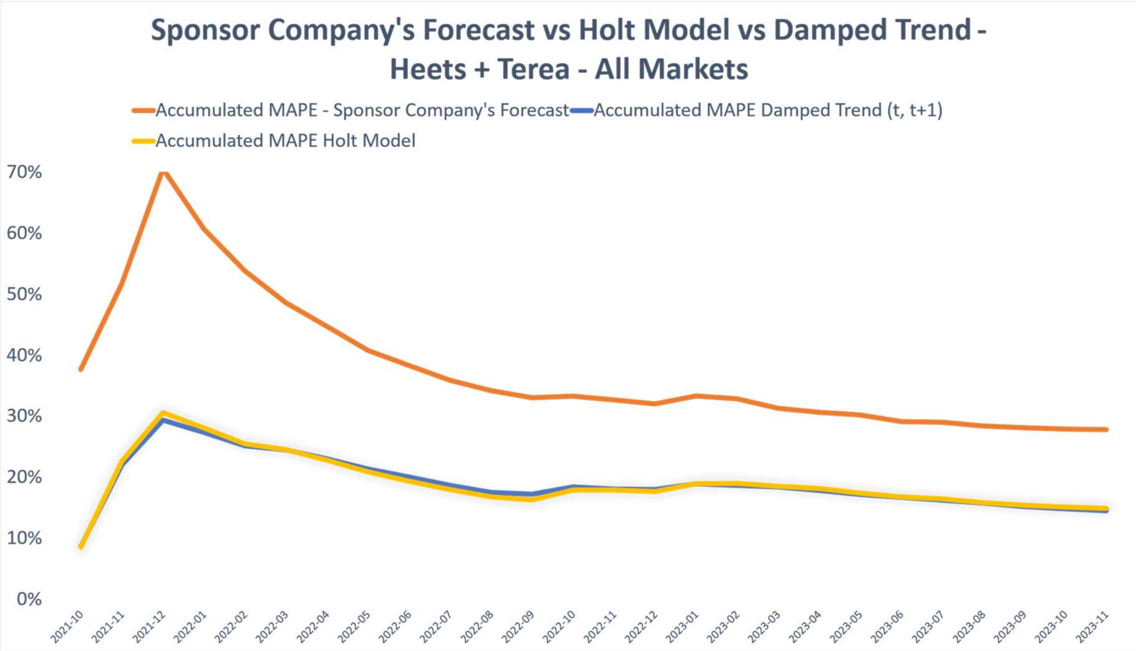
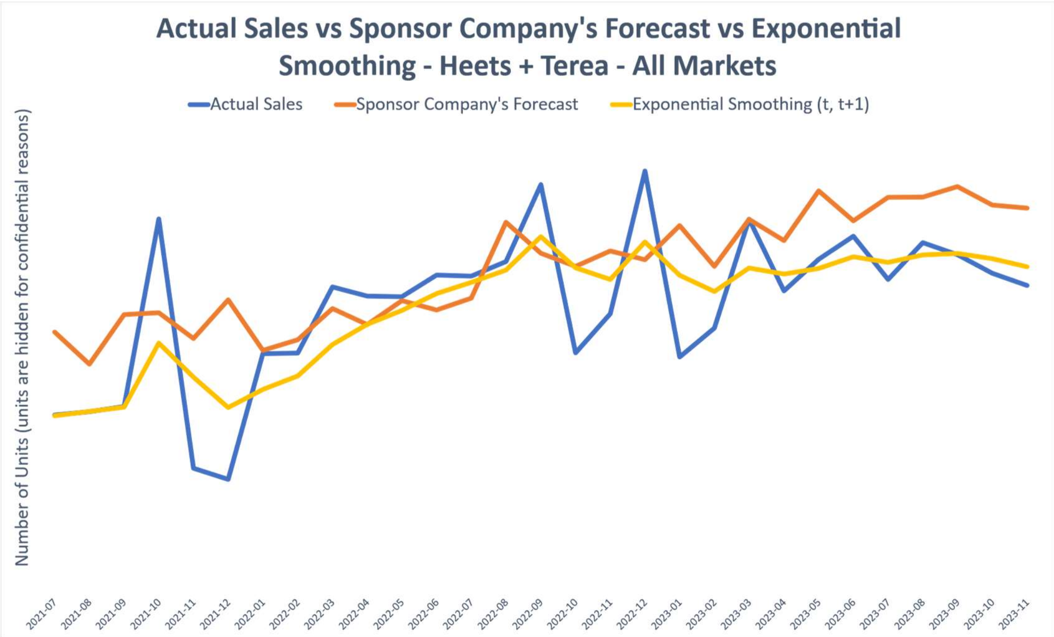


Figure B-3 illustrates that the dashed curve of the Exponential Smoothing with Damped Trend method tends to be closer to the Actual Sales line when compared to the Sponsor Company Forecast.

Figure B-3

Actual Sales vs the Sponsor Company's Forecast vs Exponential Smoothing – Heets + Terea – All Markets



B.5 Exponential Smoothing Damped Trend Forecast – Forecasting for *t+3* in Time Period *t*

Table B-6 displays the execution of the Exponential Smoothing – Damped Trend Forecast in time period *t* for time period *t*+3. This model presented an Accumulated MAPE of 20.7%, compared to 28.0% of the company's forecast.

Table B-6

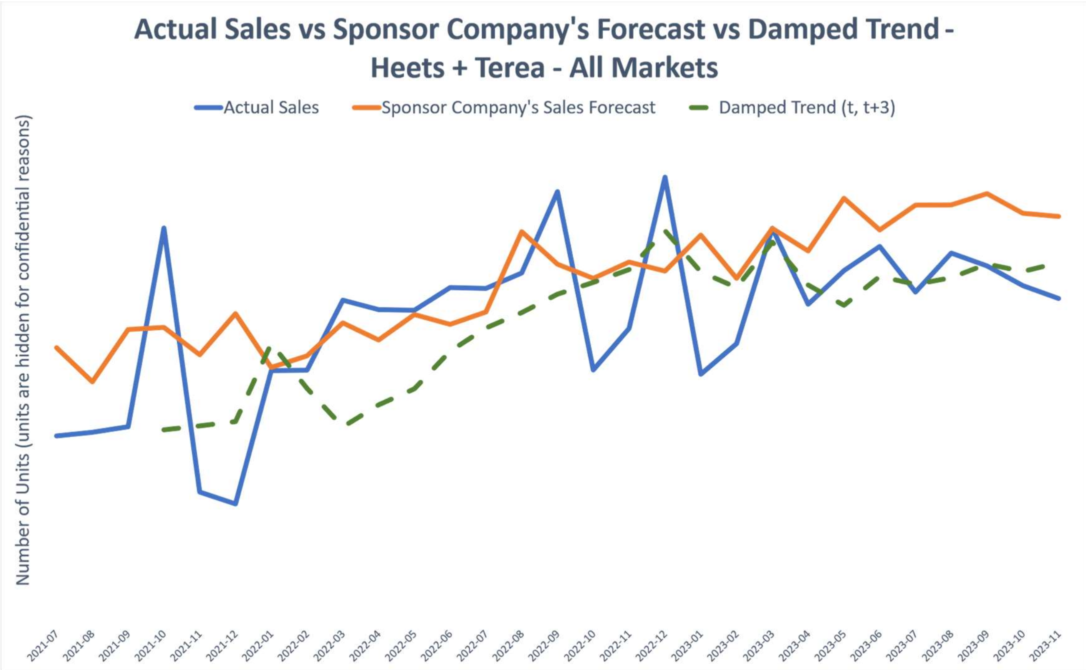
Exponential Smoothing – Damped Trend Forecast – Forecasting for t+3 in Time Period t

Date	Montlhy MAPE PMI Forecast	Accumulated MAPE PMI Forecast	MPE Damped Trend (t, t+3)	Accumulated MAPE Damped Trend (t, t+3)
2021-07	48%	48%		
2021-08	27%	28%		
2021-09	50%	29%		
2021-10	25%	29%	52%	52%
2021-11	108%	31%	52%	22.9%
2021-12	165%	35%	71%	24.6%
2022-01	1%	34%	11%	24.1%
2022-02	6%	33%	7%	23.6%
2022-03	7%	33%	40%	24.1%
2022-04	10%	32%	31%	24.3%
2022-05	1%	31%	25%	24.3%
2022-06	11%	31%	19%	24.2%
2022-07	7%	30%	12%	23.8%
2022-08	12%	30%	11%	23.5%
2022-09	17%	30%	24%	23.5%
2022-10	37%	30%	35%	23.8%
2022-11	23%	30%	20%	23.7%
2022-12	21%	29%	12%	23.4%
2023-01	57%	30%	42%	23.9%
2023-02	24%	30%	20%	23.8%
2023-03	0%	29%	4%	23.3%
2023-04	17%	29%	6%	23.0%
2023-05	21%	29%	10%	22.7%
2023-06	4%	28%	8%	22.4%
2023-07	27%	28%	2%	21.9%
2023-08	13%	28%	7%	21.6%
2023-09	20%	28%	1%	21.2%
2023-10	22%	28%	4%	20.9%
2023-11	26%	28%	11%	20.7%

Figure B-4 illustrates that the dashed curve of the Exponential Smoothing with Damped Trend method tends to be closer to the Actual Sales line when compared to the Sponsor Company Forecast.

Figure B-4

Actual Sales vs the Sponsor Company's Forecast vs Damped Trends – Heets + Terea – All Markets



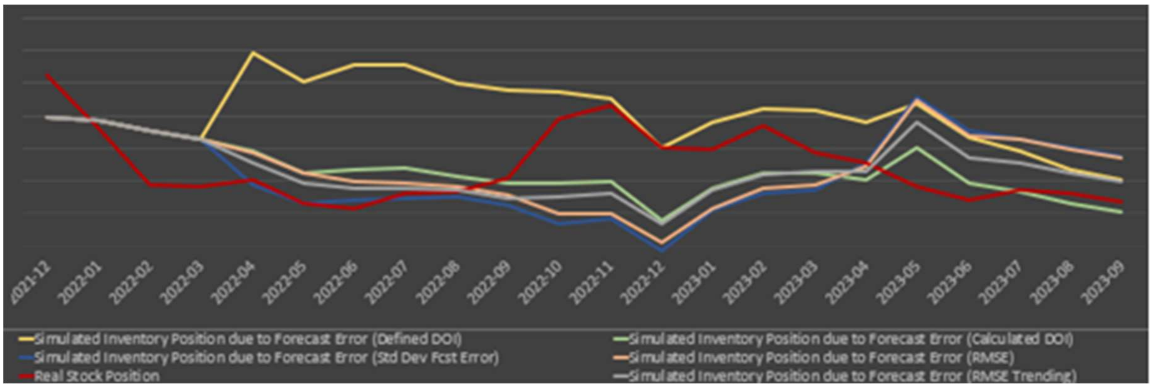
Appendix C - Simulated Inventory Position with Different Production Plans per Market

C.1 – Czech Republic

Figure D-1 shows the simulated inventory position comparing the different Production Plans in the Czech Republic market. The calculated DOI in this market was 26 days.

Figure C-1

CZECH Republic Heets Simulated Inventory Position – lead time 3 months

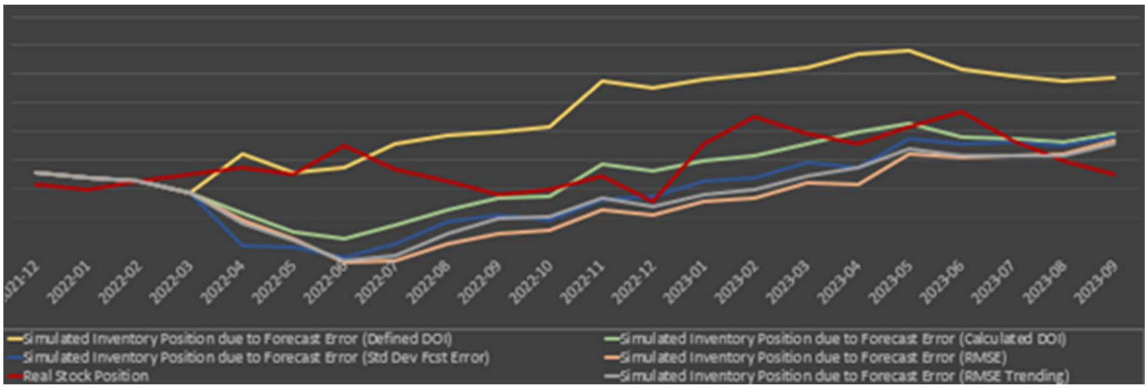


C.2 – Hungary

Figure C-2 shows the simulated inventory position comparing the different Production Plans in the Hungary market. The calculated DOI in this market was 34 days.

Figure C-2

Hungary Heets Simulated Inventory Position – lead time 3 months



C.3 – Slovak Republic

Figure C-3 shows the simulated inventory position comparing the different Production Plans in the Slovak Republic market. The calculated DOI in this market was 25 days. In this market we can see that the inventory position of the company was lower than the recommended by our policy.

Figure C-3

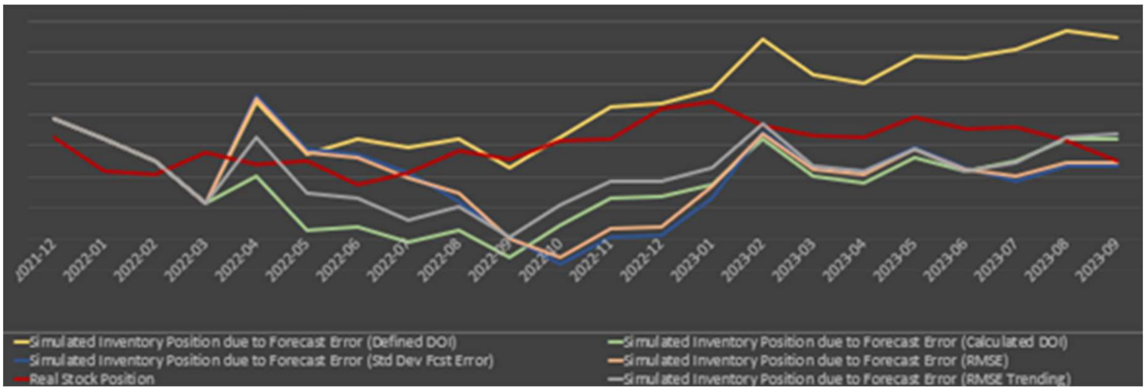
Slovak Republic Heets Simulated Inventory Position – lead time 3 months

C.4 – Poland

Figure C-4 displays the simulated inventory position comparing the different Production Plans in the Poland market. The calculated DOI in this market was 28 days. In this market, all the production plan methodologies experienced stockouts because from January 2022 until September 2022, the company sold more than forecasted in 7 out of 9 months in the period. In this case, forecast inaccuracy led to stockouts across all production plan methodologies.

Figure C-4

Poland Heets Simulated Inventory Position – lead time 3 months



Appendix D – Forecasting Equations

D.1 – Moving Average

The moving average can be calculated according to (17):

$$X_{t,t+1} = \frac{\sum_{i=(t+1-M)}^{t} Xi}{M} \tag{17}$$

Notation:

$X_{(t,t+1)}$= forecast in period t for the period t+1

M = number of months to be considered in the moving average

X_i = Actual values of the last M data points.

D.2 – Exponential Smoothing for Level and Trend (Holt Model)

The equation for this method is defined as the follows:

$$X_{t,t+T} = a_t + T * b_t \tag{18}$$

$$a_t = \alpha * x_t + (1-\alpha) * (a_{t-1} + b_{t-1}) \tag{19}$$

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta) * b_{t-1} \tag{20}$$

Notation:

$X_{(t,t+T)}$= forecast in period t for the period t+T (units)

a_t= level of sales for the time period t (units)

b_t= slope of sales for the time period t (units)

α = Exponential smoothing factor for level (0 ≤ α ≤ 1)

β = Exponential smoothing factor for trend (0 ≤ β ≤ 1)

ω = Mean Square Error trending factor (0.01 ≤ ω ≤ 1)

x_t = Actual sales for time period t (units).

D.3 – Damped Trend Model

The equation for this method is defined as the follows:

$$X_{t,t+T} = a_t + \sum_{i=1}^{t} \varphi^i * b_t \tag{21}$$

$$a_t = \alpha * x_t + (1-\alpha) * (a_{t-1} + \varphi * b_{t-1}) \tag{22}$$

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta) * \varphi * b_{t-1} \tag{23}$$

Notation:

$X_{(t,t+T)}$= forecast in period t for the period t+T (units)

a_t= level of sales for the time period t (units)

b_t= slope of sales for the time period t (units)

α = Exponential smoothing factor for level (0 ≤ α ≤ 1)

β = Exponential smoothing factor for trend (0 ≤ β ≤ 1)

φ = Exponential smoothing factor for dampening (0 ≤ φ ≤ 1)

x_t = Actual sales for time period t (units)

Appendix E – Inputs and Parameters for the Simulation Tool

Parameters for conducting scenario analysis.

Table E-1

Parameters for the Simulated Production Plan

Current Month	End Production Plan	Market	L1	Lead Time	Service Level	Review Period	Lead Time Anticipation	Lead Time Delay	Forecast Error Min	Forecast Error Max	DOI
abr-24	jun-25	Czech Republic	Heets	2	95%	1	10%	30%	30%	10%	40

Inputs for the simulation model.

Table E-2

Data Input for the Simulated Production Plan

Date	Forecast	Stock Position	Production Plan
nov-23			
dez-23			
jan-24			
fev-24			
mar-24			
abr-24			
mai-24			
jun-24			
jul-24			
ago-24			
set-24			
out-24			
nov-24			
dez-24			
jan-25			
fev-25			
mar-25			
abr-25			
mai-25			
jun-25			
jul-25			
ago-25			

Appendix F – Inventory Position For the Days of Inventory Methodologies

Table F-1

Inventory Position for the Days of Inventory Methodologies

$$Safety\ Stock = Days\ of\ Inventory * IMS$$