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Beyond MAPE: Product Mix Deviation and Inventory Response in Hierarchical Demand Forecasting

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Abstract

This paper examines how commonly used demand forecasting accuracy metrics, particularly Mean Absolute Percentage Error (MAPE), behave across hierarchical product levels in manufacturing environments and which structural operational risks may remain concealed when analysis is limited to aggregated indicators. Using a 24-month dataset of actual and forecasted demand, product mix structure, and inventory indices, the study distinguishes between volume forecast accuracy and mix forecast accuracy. The results show that while aggregate-level MAPE may appear acceptable, substantial forecast errors persist at lower hierarchy levels and are not neutralized by aggregation. A key contribution of the study is the treatment of product mix deviation as an independent source of operational risk rather than a secondary effect of volume forecast error. Empirical evidence indicates that mix deviations can persist even under high aggregate forecast accuracy and are associated with non-linear and asymmetric inventory responses. In particular, demand overestimation leads to sharper inventory increases than the reductions observed under demand underestimation. Adopting a decision-oriented perspective, the study conceptualizes forecasting dashboards as decision support systems that support managerial interpretation of forecast errors and help identify structurally hidden demand risks in operational contexts.

Keywords
Demand forecasting; MAPE; Product mix deviation; Inventory behavior; Hierarchical forecasting.

1. Introduction
Demand forecasting accuracy remains a central concern in manufacturing operations, as forecast errors directly influence production planning, inventory levels, and service performance (Silver et al. 1998; Zipkin 2000). Among various accuracy measures, Mean Absolute Percentage Error (MAPE) is one of the most widely used metrics in both academic research and managerial practice due to its simplicity and intuitive interpretation (Armstrong 2001; Hyndman and Athanasopoulos 2021). As a result, forecasting dashboards and performance reviews in many organizations rely heavily on aggregate MAPE values to assess forecast quality and guide operational decisions (Fildes and Goodwin 2007).

However, manufacturing demand is typically structured hierarchically across multiple product groups and subgroups (Athanasopoulos et al. 2009). In such environments, aggregation may conceal structurally significant deviations that are operationally relevant but statistically muted at higher levels. In particular, acceptable aggregate forecast accuracy does not necessarily imply reliable demand allocation across product mix dimensions. Forecast errors at lower hierarchy levels may persist even when overall volume accuracy appears satisfactory, potentially leading to inventory imbalances and suboptimal operational responses (Syntetos et al. 2005; Mentzer and Moon 2005).

Prior forecasting research has extensively examined error metrics, hierarchical forecasting methods, and demand uncertainty (Hyndman et al. 2008; Makridakis et al. 2018). Yet, relatively limited attention has been given to how commonly used accuracy indicators behave across hierarchy levels from a decision-making perspective, and how forecast deviations translate into operational consequences such as inventory accumulation or depletion. In practice, managers often interpret forecast accuracy metrics as sufficient signals of forecast reliability, without explicit consideration of product mix distortion (Fildes et al. 2019).

This study addresses this gap by examining the relationship between forecast accuracy, product mix deviation, and inventory behavior in a manufacturing context. Using longitudinal operational data, the paper demonstrates that product mix deviation constitutes a distinct source of operational risk that is not adequately captured by aggregate accuracy metrics. By adopting a decision-oriented perspective, the study reframes forecasting dashboards as decision support systems and highlights the limitations of relying solely on traditional forecast accuracy indicators.

The relevant literature on forecasting accuracy metrics, hierarchical forecasting, and inventory behavior is reviewed within the Introduction and Problem Formulation sections to support the decision-oriented framing of the study.

2. Problem Formulation

Forecast accuracy is commonly used as a proxy for forecast quality in manufacturing operations (Armstrong 2001; Hyndman and Athanasopoulos 2021). Among available accuracy metrics, Mean Absolute Percentage Error (MAPE) remains one of the most frequently applied indicators due to its simplicity and interpretability. In practice, MAPE values are often monitored at aggregated product levels and incorporated into forecasting dashboards, performance reviews, and operational planning routines (Fildes and Goodwin 2007; Mentzer and Moon 2005).

However, manufacturing demand is typically structured hierarchically across product groups, subgroups, and individual items (Athanasopoulos et al. 2009). In such hierarchical settings, aggregation effects may distort the informational content of accuracy metrics. While aggregation can reduce random noise and stabilize forecast errors statistically, it may also obscure structurally relevant deviations at lower hierarchy levels. As a result, acceptable aggregate forecast accuracy does not necessarily imply reliable demand allocation across the product mix (Syntetos et al. 2005).

From an operational perspective, forecast errors are not neutral. Deviations between forecasted and actual demand influence production decisions, inventory positioning, and replenishment behavior (Silver et al. 1998; Zipkin 2000). Importantly, the operational consequences of forecast errors may depend not only on total volume deviation but also on how demand is distributed across product categories. Misallocation of demand across the product mix can therefore generate inventory imbalances even when aggregate forecast accuracy appears satisfactory (Chen et al. 2000).

Existing forecasting literature has extensively examined error metrics, forecast combination methods, and hierarchical forecasting techniques (Hyndman et al. 2008; Makridakis et al. 2018). Nevertheless, limited attention has been given to how commonly used accuracy measures behave across hierarchy levels when interpreted as decision signals rather than purely statistical indicators. In particular, the relationship between forecast accuracy, product mix deviation, and inventory response remains underexplored in applied manufacturing contexts (Fildes et al. 2019).

This study formulates the forecasting problem from a decision-oriented perspective, focusing on the limitations of aggregate accuracy metrics for operational control. Rather than evaluating forecasting models or optimization techniques, the analysis examines how forecast accuracy indicators are interpreted within dashboard-based decision systems and how structurally hidden deviations may affect inventory behavior.

Based on this perspective, the study addresses the following research questions:

RQ1: How does forecast accuracy, as measured by MAPE, vary across hierarchical product levels in manufacturing demand data?

RQ2: To what extent can product mix deviation persist even when aggregate forecast accuracy appears acceptable?

RQ3: How does inventory behavior respond to forecast deviations at different hierarchy levels, and is this response symmetric with respect to demand overestimation and underestimation?

This study makes three contributions. First, it provides empirical evidence that aggregate forecast accuracy metrics such as MAPE may conceal structurally significant deviations at lower hierarchy levels in manufacturing demand systems.

Second, the study introduces product mix deviation as a distinct and operationally relevant diagnostic dimension, conceptually separate from total volume forecast error and not captured by traditional accuracy metrics.

Third, it demonstrates that inventory responses to forecast deviations are asymmetric and non-linear, reinforcing the need to interpret forecasting dashboards as decision support systems rather than purely as performance reporting tools.

By articulating the forecasting problem in this manner, the study aims to clarify the distinction between statistical forecast accuracy and operational decision relevance, thereby motivating the subsequent methodological and empirical analysis.

3. Methods

3.1 Research Design

This study adopts a design-oriented, empirical case study approach to examine how forecasting accuracy metrics are interpreted within dashboard-based decision systems in a manufacturing context. The objective is not to compare forecasting algorithms or optimize prediction accuracy, but to analyze how commonly used accuracy indicators behave across hierarchical levels and how forecast deviations translate into observable operational outcomes.

This perspective aligns with prior operations management research emphasizing decision relevance and interpretability of analytical indicators over purely statistical optimization (Fildes and Goodwin 2007; Mentzer and Moon 2005).

3.2 Analytical Framework

The analysis is structured around three interrelated analytical dimensions:

1. **Forecast accuracy across hierarchy levels**, measured using Mean Absolute Percentage Error (MAPE);
2. **Product mix deviation**, capturing discrepancies between forecasted and actual demand allocation across product groups;
3. **Inventory response**, observed through normalized inventory indices as an operational consequence of forecast deviations.

This framework reflects established distinctions between volume-based forecast evaluation and structural demand characteristics discussed in the forecasting literature (Hyndman and Athanasopoulos 2021).

3.3 Forecast Accuracy Measurement

Forecast accuracy is evaluated using Mean Absolute Percentage Error (MAPE), defined as:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{Actual_t - Forecast_t}{Actual_t} \right| \times 100\%$$

MAPE is calculated at multiple hierarchy levels, including aggregate demand, product group level, and product subgroup level. This hierarchical evaluation enables examination of aggregation effects on forecast accuracy metrics (Athanasopoulos et al. 2009).

MAPE is treated as a **diagnostic indicator** rather than a definitive measure of forecast quality, consistent with prior discussions on the limitations of single-metric forecast evaluation (Makridakis et al. 2018).

3.4 Product Mix Deviation

To complement volume-based accuracy assessment, the study explicitly measures **product mix deviation**. Product mix deviation is defined as the absolute difference between forecasted and actual demand shares for each product group or subgroup within a given period:

$$MixDeviation_{i,t} = | Share_{i,t}^{Forecast} - Share_{i,t}^{Actual} |$$

This measure captures structural misallocation of demand across the product portfolio, independent of total volume accuracy. Similar distinctions between volume accuracy and demand composition have been emphasized in prior studies of demand patterns and aggregation effects (Syntetos et al. 2005).

Unlike conventional disaggregated forecast error metrics, product mix deviation focuses on relative demand allocation across product categories rather than absolute forecast errors. The measure is inherently normalized by total demand, which allows comparison across time periods and hierarchy levels without being driven by scale effects. As a result, product mix deviation captures structural allocation distortions that may persist even when aggregate or item-level forecast accuracy appears acceptable.

3.5 Inventory Response Measurement

Operational consequences of forecast deviations are assessed using a normalized inventory index, representing relative changes in inventory levels over time. Inventory management literature consistently highlights the sensitivity of inventory behavior to forecast uncertainty and demand misalignment (Silver et al. 1998; Zipkin 2000).

Rather than estimating causal effects, the analysis examines directional and asymmetric responses of inventory behavior to forecast deviations, focusing on differences between demand overestimation and underestimation scenarios.

3.6 Analysis Procedure

The empirical analysis follows a structured multi-step procedure:

1. Calculation of forecast accuracy metrics (MAPE) across hierarchy levels;
2. Measurement of product mix deviation at corresponding levels;
3. Examination of inventory index behavior over time;
4. Joint analysis of forecast deviations, mix deviation, and inventory response;
5. Identification of systematic patterns, including asymmetry and non-linearity in inventory behavior.

All analyses are conducted using monthly aggregated data to ensure consistency and robustness across planning cycles.

3.7 Scope and Limitations of the Method

The proposed method is intentionally descriptive and diagnostic. It does not aim to establish causal relationships or evaluate forecasting model superiority. Instead, it provides empirical evidence on how commonly used forecasting metrics may obscure structurally important operational risks when interpreted in isolation.
This methodological positioning is consistent with applied operations management research that prioritizes interpretability and decision relevance over algorithmic optimization (Fildes et al. 2019).

4. Data Collection

4.1 Data Source and Scope

The empirical analysis is based on operational data obtained from a manufacturing organization operating in a volatile demand environment. The dataset covers a **24-month period** with **monthly aggregation**, ensuring consistency across planning and reporting cycles.

Data were extracted from internal forecasting and inventory monitoring systems used for routine operational decision-making. The study focuses on demand planning outputs and observed inventory behavior rather than on transactional or customer-level data.

The scope of the dataset includes multiple hierarchical levels of demand aggregation:

- total demand level,
- product group level,
- product subgroup level.

This hierarchical structure enables systematic examination of aggregation effects on forecast accuracy metrics and operational outcomes.

The data originate from a discrete manufacturing context characterized by a diversified product portfolio and medium-to-high demand variability across product categories. The demand hierarchy includes multiple product groups and subgroups, representing several hundred active stock-keeping units (SKUs). While product-level details are not disclosed for confidentiality reasons, the structure is representative of manufacturing environments where forecast accuracy is routinely monitored at aggregated levels for planning and control purposes.

4.2 Forecast and Inventory Data

For each period and hierarchy level, the following data elements were collected:

- forecasted demand volumes,
- actual demand volumes,
- product mix shares (forecasted and actual),
- inventory levels.

To preserve confidentiality and avoid disclosure of commercially sensitive information, all volume and inventory measures were transformed into normalized indices. Absolute values, prices, revenues, margins, customer identifiers, and order-level data were explicitly excluded from the dataset.

Inventory levels are represented using a relative inventory index, capturing directional changes and temporal dynamics rather than absolute stock quantities.

4.3 Data Transformation and Normalization

All numerical measures were transformed prior to analysis using the following principles:

- monthly aggregation to reduce noise and ensure temporal alignment;
- normalization of demand and inventory values into indices;
- anonymization of product identifiers and grouping into generic product categories.

These transformations allow comparison across periods and hierarchy levels while maintaining data confidentiality. Importantly, normalization preserves relative variation and structural patterns required for diagnostic analysis, even though absolute magnitudes are not disclosed.

4.4 Measurement Construction

Based on the transformed dataset, the following analytical measures were constructed:

- **Forecast accuracy**, measured using MAPE at each hierarchy level;
- **Product mix deviation**, calculated as the absolute difference between forecasted and actual demand shares;
- **Inventory response**, observed through changes and volatility in the inventory index.

All measures were computed consistently across hierarchy levels and time periods to ensure comparability.

4.5 Ethical Considerations and Data Confidentiality

The study does not involve human subjects, surveys, interviews, or experimental interventions. All data are operational in nature, aggregated, anonymized, and transformed prior to analysis. No personal, customer, or employee-level information is included.

Given the use of fully anonymized and index-based operational data, formal ethical approval or informed consent procedures were not required. The data collection and analysis process complies with standard ethical practices for applied operations management research.

4.6 Data Limitations

While the dataset provides sufficient depth to examine hierarchical forecast accuracy, product mix deviation, and inventory behavior, it does not include certain operational variables such as backlog levels, lead times, or explicit operational complexity indicators. As a result, the analysis focuses on observable demand and inventory patterns rather than on detailed process-level dynamics.

These limitations are explicitly acknowledged and reflected in the study's descriptive and diagnostic research design.

5. Results and Discussion

5.1 Numerical Results

This section presents numerical results summarizing forecast accuracy, product mix deviation, and inventory behavior across the observation period. To ensure clarity and readability, the analysis focuses on aggregated summary statistics rather than period-by-period operational data.

Table 1. Forecast accuracy (MAPE) across hierarchy levels

Hierarchy level	Average MAPE (%)	Minimum	Maximum
Aggregate	9%	0%	35%
Product group	43%	0%	838%
Product subgroup	148%	0%	27900%

Table 1 reports forecast accuracy measured by Mean Absolute Percentage Error (MAPE) across three hierarchical demand levels: aggregate demand, product groups, and product subgroups. The results demonstrate a clear degradation of forecast accuracy as demand data is disaggregated. While aggregate-level MAPE remains relatively low, forecast errors increase substantially at group and subgroup levels, highlighting the masking effect of aggregation on forecast performance.

Table 2. Product mix deviation summary statistics

Metric	Value
Average mix deviation (%)	2,1%
Minimum mix deviation (%)	0,3%
Maximum mix deviation (%)	5,0%
Periods with deviation > 2% (%)	37,5%

Table 2 summarizes product mix deviation over the 24-month period. The results indicate that product mix deviation persists even during periods when aggregate forecast accuracy remains within acceptable levels. Average mix deviation is accompanied by substantial variability, with several periods exhibiting deviations exceeding 1%. These findings suggest that acceptable aggregate forecast accuracy does not necessarily imply reliable demand allocation across the product mix.

Table 3. Inventory index behavior under forecast deviations

Scenario	Average index	Min	Max
All periods	199	141	331
Demand overestimation	215	141	331
Demand underestimation	176	143	227

Table 3 presents summary statistics of inventory index behavior over the full observation period. The results reveal asymmetric and non-linear inventory responses to forecast deviations. Inventory accumulation during periods of demand overestimation is more pronounced than inventory reduction during periods of demand underestimation. This asymmetry indicates that inventory dynamics respond to forecast errors in a manner that is not proportional or symmetric.

Taken together, the numerical results demonstrate that forecast accuracy metrics, product mix deviation, and inventory behavior capture different dimensions of forecasting performance. In particular, aggregation conceals structurally relevant deviations that manifest at lower hierarchy levels and translate into operational instability.

5.2 Graphical Results

Graphical analysis is used to complement the numerical results by illustrating structural patterns that are not fully captured by summary statistics. The figures emphasize hierarchy effects, variability, and non-linear responses rather than precise point estimates.

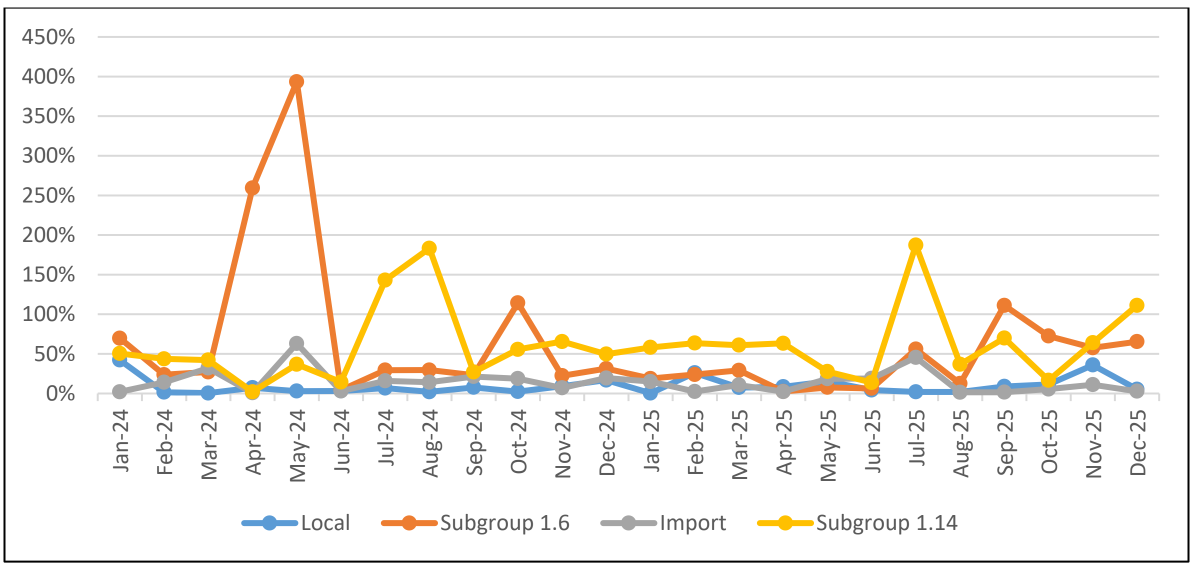

Figure 1. MAPE Dynamics

Figure 1 illustrates forecast accuracy dynamics across selected representative hierarchy levels. Due to readability constraints, the figure displays aggregate demand and a subset of product subgroups rather than the full hierarchy. Despite this limitation, the figure clearly demonstrates the divergence between aggregate-level stability and increased variability at lower hierarchy levels, consistent with the numerical results reported in Table 1. (Athanasopoulos et al. 2009).

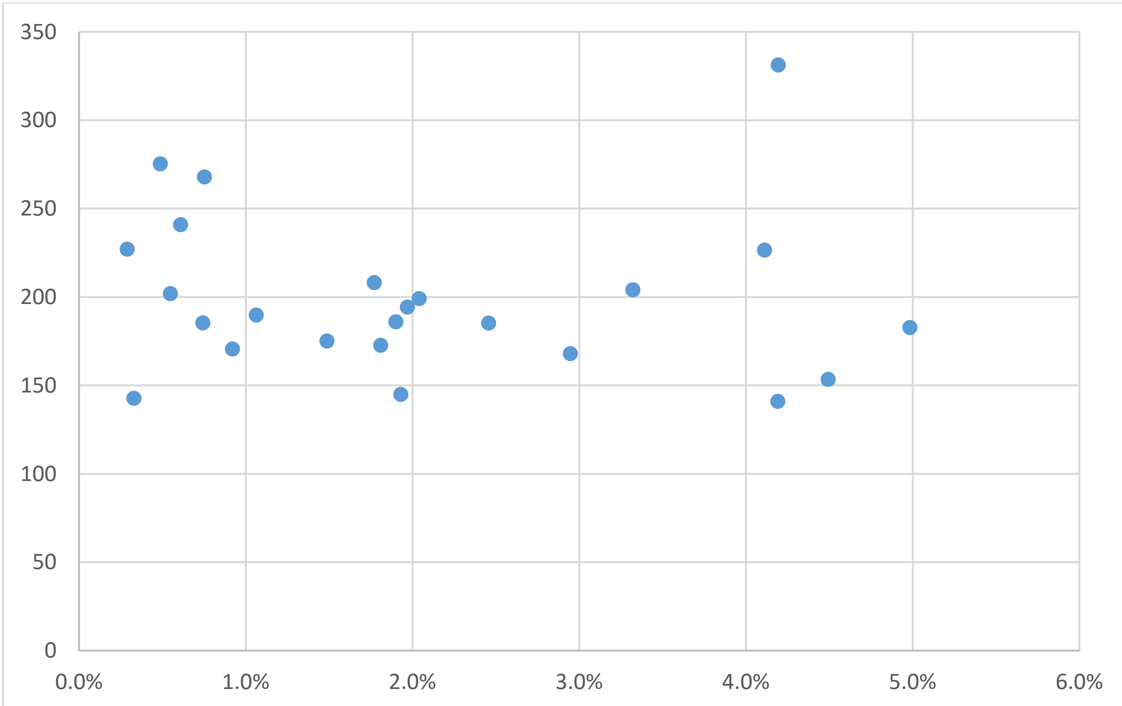

Figure 2. Mix deviation vs inventory index

Figure 2 presents the relationship between product mix deviation and changes in the inventory index. The scatter plot does not indicate a strong linear relationship between the two variables. Instead, the figure highlights increasing dispersion of inventory outcomes as product mix deviation grows. This pattern suggests that product mix deviation contributes to inventory instability rather than predictable directional changes, reinforcing its interpretation as a structural risk factor rather than a linear driver of inventory levels.

Importantly, the absence of a strong linear correlation does not imply the absence of operational relevance. In the observed manufacturing context, inventory levels are subject to operational constraints, safety stock policies, and managerial interventions, which limit proportional responses to forecast deviations. As a result, inventory indices may fluctuate within bounded ranges even under increasing product mix deviation. The growing dispersion of inventory outcomes therefore reflects rising operational instability rather than a deterministic functional relationship. This reinforces the interpretation of product mix deviation as a structural risk factor rather than a variable suited for linear modeling.

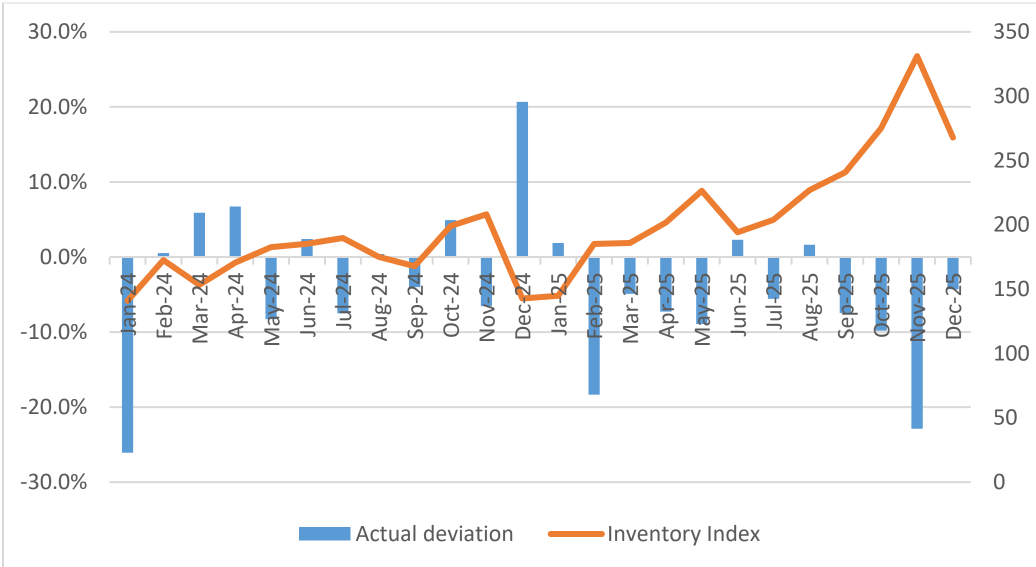

Figure 3. Inventory response

Figure 3 illustrates inventory index behavior under demand overestimation and underestimation scenarios. The graphical results reveal asymmetric inventory responses, with inventory accumulation following demand overestimation being more pronounced than inventory reduction following underestimation. This asymmetry aligns with the numerical patterns reported in Table 3 and underscores the non-linear nature of inventory dynamics.

Overall, the graphical results reinforce the numerical findings by demonstrating that aggregation conceals structurally relevant deviations and that operational responses to forecast errors are non-linear and asymmetric. These observations motivate the need for enhanced decision-oriented forecasting dashboards, discussed in the subsequent section.

5.3 Proposed Improvements

Based on the empirical results, this section proposes several improvements aimed at enhancing the decision relevance of forecasting dashboards in manufacturing operations. The focus is not on improving forecasting models, but on improving how forecast accuracy information is interpreted and used in operational decision-making.

First, forecasting dashboards should explicitly distinguish between aggregate volume accuracy and structural accuracy across the product mix. Reliance on aggregate MAPE alone may create a false sense of forecast reliability, as acceptable volume accuracy can coexist with substantial product mix deviation. Introducing hierarchy-level accuracy views enables earlier identification of structurally relevant deviations.

Second, product mix deviation should be monitored as an explicit analytical dimension rather than inferred indirectly from forecast accuracy metrics. Simple mix deviation indicators can be integrated into existing dashboards without requiring additional forecasting complexity. This allows managers to detect misallocation risks that are otherwise concealed by aggregation.

Third, inventory behavior should be interpreted as an operational response signal rather than as a direct validation of forecast accuracy. The observed asymmetry and non-linearity in inventory responses suggest that inventory dynamics provide additional contextual information that complements forecast accuracy metrics, particularly under demand volatility.

Collectively, these improvements reposition forecasting dashboards from static performance reporting tools to decision support systems that better reflect the structural and operational realities of manufacturing demand. Such an approach enhances managerial interpretation without increasing analytical complexity.

5.4 Validation

Validation of the results focuses on consistency, robustness, and interpretability rather than statistical hypothesis testing. Several internal consistency checks were performed to ensure that the observed patterns are not driven by isolated periods or specific aggregation choices.

First, the analysis was repeated across different hierarchy levels, confirming that forecast accuracy degradation and product mix deviation persist beyond the aggregate level. Second, the observed inventory response patterns were examined across multiple sub-periods within the 24-month window, yielding qualitatively similar results. Third, alternative threshold values for product mix deviation were tested, confirming that the main findings are robust to reasonable changes in parameter assumptions.

Overall, the validation results support the stability of the observed relationships and reinforce the interpretation of product mix deviation and inventory behavior as structurally relevant operational phenomena rather than artefacts of data aggregation or metric selection.

6. Conclusion

This study examined the limitations of commonly used forecast accuracy metrics when applied as decision signals in manufacturing operations. Focusing on a dashboard-based decision context, the analysis demonstrated that acceptable aggregate forecast accuracy may coexist with substantial product mix deviation and asymmetric inventory responses.

The results highlight that forecast accuracy, product mix deviation, and inventory behavior capture distinct dimensions of forecasting performance. In particular, aggregation conceals structurally relevant deviations at lower hierarchy levels, while inventory dynamics respond to forecast errors in a non-linear and asymmetric manner. These effects are not adequately reflected by aggregate accuracy indicators such as MAPE.

By adopting a decision-oriented perspective, the study reframes forecasting dashboards as decision support systems rather than static performance reporting tools. The findings suggest that enhancing interpretability—through hierarchy-level views, explicit monitoring of product mix deviation, and inventory-aware interpretation—can improve operational decision-making without increasing analytical complexity.

The study is subject to limitations, including reliance on aggregated operational data from a single manufacturing context and the absence of causal inference. Nevertheless, the results provide empirical evidence that structural demand characteristics and operational responses should be explicitly considered alongside traditional forecast accuracy metrics. Future research may extend this approach to other industries, alternative demand structures, and broader decision environments.

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Biographies

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Alexey Nuzhnyy is an independent researcher and senior executive with over twenty years of experience in finance, operations, and performance management in global industrial organizations. His background covers manufacturing, energy, and complex industrial sectors, with a focus on demand planning, forecasting evaluation, inventory management, and decision-making under uncertainty.

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Alexander Zhidkov
Alexander Zhidkov is an independent researcher specializing in business intelligence, data analytics, and decision support systems. He has extensive experience in designing and implementing analytical platforms that support operational and managerial decision-making.

His background spans multiple industries, including IT and FMCG, with a focus on forecasting dashboards, data integration, and performance monitoring systems. His work emphasizes data quality, interpretability, and the practical usability of metrics.

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