CAPÍTULO 04

THE MARGIN FORECASTING FRAMEWORK (MFF): AN OPERATIONS ANALYTICS APPROACH FOR INDUSTRIAL EQUIPMENT IN THE FOOD & BEVERAGE SECTOR

Thiago Martins Nunes
Master of Business Administration
University of Minnesota
E-mail: nunes045@umn.edu

ABSTRACT: Accurate forecasting of revenue and operating margin is one of the most critical challenges in business-to-business (B2B) capital equipment industries, including food and beverage (F&B) manufacturing equipment providers such as Tetra Pak, GEA, and Krones. Traditional forecasting methods, including time-series models and regression-based approaches, often fail to capture the operational complexity of industries characterized by long project lead times, large backlogs, and diverse revenue recognition mechanisms under Generally Accepted Accounting Principles (GAAP). This article introduces a structured framework for forecasting revenue and margin in B2B equipment sales that integrates four categories of revenue sources: (1) backlog orders, (2) in-month orders (book-and-turn), (3) accounting adjustments such as deferred revenue, and (4) GAAP-compliant leasing and service revenues. By disaggregating revenue and margin at the category level, the framework provides higher accuracy and actionable visibility into core revenue growth and operating margin. A case study demonstrates its application in a U.S.-based industrial equipment firm, where forecast accuracy improved from 85% to 92% during a tariff mitigation crisis. This contribution highlights the importance of integrating operational and financial data sources—such as enterprise resource planning (ERP) and customer relationship management (CRM) systems—into forecasting methodologies, offering an original approach that strengthens financial planning and decision-making in capital equipment industries.

KEYWORDS: operations analytics, food and beverage industry, forecasting.

RESUMO: A previsão precisa da receita e da margem operacional é um dos desafios mais críticos nos setores de equipamentos de capital business-to-business (B2B), incluindo fornecedores de equipamentos para fabricação de alimentos e bebidas (F&B), como Tetra Pak, GEA e Krones. Métodos tradicionais de previsão, incluindo modelos de séries temporais e abordagens baseadas em regressão, frequentemente falham em capturar a complexidade operacional de setores caracterizados por longos prazos de entrega de projetos, grandes pendências e diversos mecanismos de reconhecimento de receita de acordo com os Princípios Contábeis Geralmente Aceitos (GAAP). Este artigo apresenta uma estrutura para previsão de receita e margem em vendas de equipamentos B2B que integra quatro categorias de fontes de receita: (1) pedidos em carteira, (2) pedidos mensais (book-and-turn), (3) ajustes contábeis, como receita diferida, e (4) receitas de leasing e serviços em conformidade com os GAAP. Ao desagregar a receita e a margem no nível da categoria, a estrutura

fornece maior precisão e visibilidade acionável sobre o crescimento da receita principal e a margem operacional. Um estudo de caso demonstra sua aplicação em uma empresa de equipamentos industriais sediada nos EUA, onde a precisão das previsões aumentou de 85% para 92% durante uma crise de mitigação tarifária. Esta contribuição destaca a importância da integração de fontes de dados operacionais e financeiros — como sistemas de planejamento de recursos empresariais (ERP) e gestão de relacionamento com o cliente (CRM) — em metodologias de previsão, oferecendo uma abordagem original que fortalece o planejamento financeiro e a tomada de decisões em indústrias de equipamentos de capital.

PALAVRAS-CHAVE: análise de operações, indústria de alimentos e bebidas, previsão.

1. INTRODUCTION

Forecasting financial performance is a cornerstone of corporate strategy and capital markets communication. Among the most scrutinized indicators in quarterly and annual reporting are core revenue growth and operating margin, which signal not only the immediate financial health of a firm but also its ability to generate long-term value (Koller, Goedhart, & Wessels, 2020). For firms in the business-to-business (B2B) capital equipment industry, especially those serving food and beverage (F&B) manufacturing, forecasting these indicators presents unique challenges. Unlike consumer goods firms that experience high transaction volumes and short lead times, capital equipment providers typically manage complex projects with extended delivery cycles, substantial backlogs, and multifaceted revenue recognition requirements.

The F&B manufacturing industry is particularly relevant because it sits at the intersection of global food security, sustainability imperatives, and industrial innovation. Equipment providers such as Tetra Pak, GEA, and Krones supply the infrastructure that enables efficient production, processing, and packaging. These firms operate in an environment characterized by high capital intensity, strict regulatory compliance, and increasing demand for sustainability-driven innovation. Accurate revenue and margin forecasting in this sector is therefore critical not only for internal decision-making but also for external stakeholders, including investors, regulators, and customers.

Despite the importance of forecasting, many industrial equipment firms rely heavily on traditional forecasting techniques such as linear regression, exponential smoothing, or ARIMA models. While statistically robust, these methods are often insufficient in capturing the granular operational dynamics of B2B environments. For instance, they may not account for the recognition of large backlog orders with variable lead times, or the interplay between in-month orders and deferred revenue adjustments. As Makridakis, Spiliotis, and Assimakopoulos (2018) argue, purely statistical models can be limited in volatile or complex business environments unless complemented with domain knowledge and operational data.

This article proposes a novel forecasting framework designed specifically for B2B equipment industries with large backlogs and long project cycles. The framework categorizes revenue sources into four distinct streams:

1. Backlog Margin and Top Line – previously booked orders pending shipment, segmented into run-rate deals and large deals.
2. In-Month Orders (Book & Turn) – orders booked and shipped within the same fiscal month.
3. Accounting Adjustments – deferred revenue, reclassifications, or accruals carried over from previous periods.
4. GAAP-Compliant Leasing and Service Revenues – revenues recognized under different accounting rules, such as equipment leasing or service contracts.

Each category is linked to both revenue and margin, allowing for a consolidated forecast of top line and margin percentage. This disaggregation not only increases forecast accuracy but also improves managerial decision-making by providing transparency into the drivers of profitability.

The contribution of this framework is twofold. First, it demonstrates that operational data from ERP and CRM systems—often underutilized in forecasting—can be systematically leveraged to increase accuracy. Second, it provides a replicable methodology that can be applied across industries with similar dynamics, such as industrial automation, medical devices, and aerospace. A case study from a Chicago-based B2B equipment provider illustrates the framework's effectiveness, showing an improvement in forecast accuracy from 85% to 92% during a period of heightened uncertainty caused by tariff changes on raw materials.

By bridging the gap between financial forecasting and operational analytics, this framework represents an original contribution to the field of industrial engineering and financial management. It underscores the need for integrated forecasting models that reflect the realities of modern B2B industries, where backlog management, customer funnel dynamics, and accounting rules converge to determine financial outcomes.

2. THEORETICAL FRAMEWORK

Forecasting revenue and margin in capital equipment industries has been the subject of increasing academic and managerial attention. Unlike high-frequency industries such as retail, where vast transactional datasets allow for the application of robust time-series and machine learning models, B2B capital equipment sales are defined by long lead times, customized projects, and complex revenue recognition structures. This section reviews three relevant streams of literature: (1) statistical

forecasting methods, (2) judgmental adjustments and organizational forecasting practices, and (3) revenue recognition under accounting standards such as GAAP and IFRS.

2.1 STATISTICAL FORECASTING METHODS

Traditional statistical methods, such as autoregressive integrated moving average (ARIMA), exponential smoothing, and regression-based models, have long been used in corporate forecasting. These methods rely on historical data to project future outcomes under the assumption of stable patterns (Hyndman & Athanasopoulos, 2018). However, in environments where revenues depend on irregular backlog fulfillment, order variability, and exogenous shocks (e.g., tariff changes or supply chain disruptions), their predictive power is limited. Makridakis, Spiliotis, and Assimakopoulos (2018) demonstrate that while machine learning approaches outperform traditional statistical models in certain high-volume contexts, they remain vulnerable in low-frequency, high-value domains such as capital equipment sales.

Figure 1 illustrates this gap using a stylized dataset from a B2B equipment provider. While traditional statistical models projected a relatively smooth revenue trend, actual revenues displayed significant deviations due to backlog timing and large deal recognition. This reinforces the argument that **purely statistical methods fail to capture operational dynamics** critical for forecasting in B2B environments.

This limitation underscores the need for forecasting frameworks that integrate not only historical statistical patterns but also operational insights derived from ERP and CRM systems. Without considering operational data, statistical forecasts often misrepresent both revenue timing and associated margins in industries where backlog and project complexity drive outcomes.

2.2 JUDGMENTAL ADJUSTMENTS AND ORGANIZATIONAL PRACTICES

Another strand of research emphasizes the role of judgmental adjustments in organizational forecasting. Fildes, Goodwin, Lawrence, and Nikolopoulos (2009) argue that statistical forecasts alone are rarely sufficient for decision-making in industrial settings. Managers frequently adjust forecasts based on knowledge of specific deals,

customer relationships, or macroeconomic conditions. While such adjustments can improve accuracy, they may also introduce biases, particularly optimism bias in sales forecasts (Goodwin, 2010).

In capital equipment industries, judgmental adjustments are particularly common when assessing the probability of closing large deals or estimating shipment timing for backlog projects. Forecast accuracy depends on combining structured statistical methods with expert judgment. Yet, as several studies note (Moritz, 2014; Sanders & Ritzman, 2004), organizations often lack systematic frameworks that integrate judgment with quantitative models in a replicable manner. This gap provides an opportunity for frameworks—like the one proposed in this paper—that codify operational practices into structured categories of revenue sources.

2.3 REVENUE RECOGNITION UNDER GAAP AND IFRS

A third critical dimension of forecasting relates to revenue recognition rules. Under GAAP and IFRS 15 (*Revenue from Contracts with Customers*), revenue may be recognized over time or at a point in time, depending on contract structure, performance obligations, and delivery milestones (PwC, 2021). In capital equipment industries, this creates substantial complexity. For instance, long-term service contracts, leasing arrangements, and deferred revenue from partial shipments require different recognition schedules, which complicates forecasting.

Scholars and practitioners alike emphasize that forecast models ignoring accounting treatments may systematically over- or under-estimate revenue and margin (Gebhardt & Novotny-Farkas, 2011). Therefore, accurate forecasting requires explicit integration of accounting categories into the model, rather than relying solely on order intake or shipment data.

2.4 GAP IN THE LITERATURE

Taken together, the literature reveals important limitations in current approaches:

1. Statistical models struggle in contexts with irregular, project-driven revenue flows.

2. Judgmental adjustments, while valuable, often lack formal structure and reproducibility.
3. Revenue recognition rules introduce accounting-based complexity that is seldom incorporated into forecasting frameworks.

The present study addresses this gap by introducing a structured four-category framework—backlog, in-month orders, accounting adjustments, and GAAP-compliant leasing/service revenues—that integrates operational data sources with accounting realities. This approach represents a hybrid between statistical analysis and managerial judgment, designed to increase accuracy while remaining practical and replicable across B2B equipment industries.

3. METHODOLOGY

3.1 FRAMEWORK OVERVIEW

The forecasting framework developed in this study disaggregates total revenue into four categories that reflect both operational dynamics and accounting realities in B2B equipment sales:

1. Backlog Margin and Top Line – Orders already booked but not yet shipped, divided into *run-rate deals* and *large deals*.
2. In-Month Orders (Book & Turn) – New orders that are both booked and shipped within the same fiscal month.
3. Accounting Adjustments – Deferred revenue, reclassifications, or accruals from prior periods.
4. GAAP-Compliant Revenues – Leasing and service revenues recognized under distinct GAAP/IFRS 15 rules.

For each category, both Top Line Revenue and Margin ($ and %) are calculated, allowing managers to consolidate a more accurate forecast of financial performance. This disaggregation ensures that forecast accuracy does not depend on a single statistical model but instead integrates operational, financial, and accounting data sources.

3.2 BACKLOG FORECASTING

Backlog represents the most substantial and predictable portion of revenue in capital equipment industries. Yet, backlog realization rates vary between run-rate deals (routine, smaller transactions) and large deals (complex projects with longer lead times).

- Run-Rate Deals: The method recommends calculating the *average historical realization rate* over the past 36 months.
- Example: If backlog entering March totals $5M and historical data shows that, on average, 65% of run-rate backlog is shipped within the same month, the backlog revenue forecast is:

Forecast Revenue Run Rate = 0.65 × $5,000,000 = $3,250,000 Forecast\Revenue_{RunRate} = 0.65\times\$5,000,000 = \$3,250,000 Forecast Revenue Run Rate = 0.65 × $5,000,000 = $3,250,000

- Large Deals: Each deal must be individually reviewed by the finance and operations team, considering engineering complexity, customer readiness, and logistics. This manual adjustment is critical to avoid overestimating revenues from large, high-risk contracts.

Margin is then derived by applying historical cost-to-revenue ratios from ERP systems (e.g., Oracle, SAP), ensuring both gross margin dollars and percentages are captured.

3.3 IN-MONTH ORDERS (BOOK & TURN)

In-month orders are highly sensitive to sales performance and customer buying cycles. Forecasting them requires leveraging **CRM data** (e.g., Salesforce, Microsoft Dynamics).

Key inputs include:

1. Total Funnel × Hit Rate – The pipeline value multiplied by the probability of closure, based on historical conversion rates.
2. Close Date – Ensuring only opportunities within the fiscal month are included.
3. Margin Data – Pulled from CRM pricing modules or linked cost models.

Formula:

Forecast Revenue In Month = Pipeline Value × Hit Rate Forecast\Revenue_{InMonth} = Pipeline\ Value \times Hit\ Rate Forecast Revenue In Month= Pipeline Value × Hit Rate

By calculating both revenue and margin for this category, the firm captures the incremental contribution of “book-and-turn” deals.

3.4 ACCOUNTING ADJUSTMENTS

Accounting adjustments include deferred revenue recognized in the current month, accruals, or reclassifications. For example, a $200k deferred revenue item from February would increase March’s forecast without being tied to new backlog or orders.

These adjustments are essential because ignoring them often leads to underestimation of recognized revenue, particularly in industries where multi-phase projects and milestone billing are common.

3.5 GAAP-COMPLIANT REVENUES (LEASING & SERVICES)

Under GAAP/IFRS 15, leasing contracts and service agreements are recognized differently from equipment shipments.

- Leasing Revenue: Typically recognized on a straight-line basis over the contract duration.
- Service Revenue: Often exhibits higher margins (70–80%), recognized as services are rendered.

Including these categories ensures compliance with financial reporting standards and provides more realistic operating margin projections.

3.6 CONSOLIDATED FORECAST TABLE

Table 1. Consolidated forecast

Category	Top Line ($000s)	Margin ($000s)	Margin %	Data Source
Backlog	1,547	987	64%	ERP (Oracle, SAP)
Orders In-Month	2,450	1,845	75%	CRM (SFDC, Dynamics)
Service/Leasing	985	748	76%	CRM / GAAP records
Projected	4,982	3,580	71.9%	Consolidated

Source: Authors

3.7 INNOVATION OF THE FRAMEWORK

The originality of this framework lies in combining operational backlog analysis, CRM-based opportunity forecasting, accounting adjustments, and GAAP categories into a single structured model. Unlike traditional approaches that treat forecast as a statistical extrapolation, this framework:

1. Provides granular visibility across revenue sources.
2. Enhances forecast accuracy by separating predictable backlog from uncertain in-month orders.
3. Integrates judgmental review of large deals while maintaining structured statistical inputs for run-rate transactions.
4. Aligns with accounting principles, ensuring forecasts match how revenue will be reported externally.

3.8 CASE STUDY

To evaluate the applicability of the proposed forecasting framework, a case study was conducted with a U.S.-based Fortune 500 industrial equipment provider headquartered in the Chicago metropolitan area. The firm operates in the printing, coding, and marking equipment segment, supplying food, beverage, and pharmaceutical manufacturers across North America and Europe. With annual revenues exceeding $1.5 billion and a backlog routinely above $50 million per month, the company represents a typical B2B equipment provider characterized by long sales cycles, complex projects, and diverse revenue recognition mechanisms.

At the time of the study, the organization faced significant disruption due to the tariff mitigation crisis, as new import tariffs on steel and aluminum increased input costs and extended project lead times. These conditions created volatility in both backlog conversion and new order closings, complicating financial planning. Prior to adopting the framework, the company's forecasting method relied primarily on statistical extrapolation supplemented by judgmental inputs from sales managers. While this approach offered directional guidance, it systematically failed to distinguish between predictable backlog revenues and volatile in-month bookings. Forecast accuracy averaged 85%, with forecast variances frequently exceeding $4 million per month.

By implementing the four-category framework, the finance and operations team restructured their forecasting process as follows:

- Backlog segmentation: The firm analyzed over 148 open opportunities per month, splitting run-rate backlog from large deals. Historical realization rates (65–70%) were applied to run-rate items, while large deals were reviewed manually to account for engineering complexity and customer readiness.
- In-month orders: CRM data (Salesforce) was leveraged to evaluate a funnel of approximately $20 million per quarter, applying hit rates based on three-year historical conversion patterns.
- Accounting adjustments: Deferred revenues averaging $1.2 million per month were incorporated into forecasts, correcting prior underestimation of GAAP-recognized revenue.
- Service and leasing revenues: Margin-rich service contracts (~75% gross margin) and equipment leases were explicitly included, improving visibility into recurring revenues.

After three forecasting cycles, forecast accuracy improved from 85% to 92%, with the average monthly variance reduced to less than $2 million. More importantly, the structured approach provided strategic benefits:

- The finance team was able to revise quarterly investor guidance with greater confidence, strengthening credibility in earnings calls.
- Operations teams adjusted procurement and production schedules to anticipate tariff-related cost fluctuations, reducing supply chain exposure.
- Senior management gained clarity on the profitability mix between backlog-driven shipments and high-margin service revenues.

As one senior finance leader noted, the framework provided “unprecedented clarity in separating stable backlog realization from the volatility of in-month orders, allowing management to focus discussions on strategic trade-offs rather than debating forecast reliability.”

This case illustrates not only the practical value of the framework in enhancing forecast accuracy, but also its strategic importance in aligning financial guidance, operations planning, and investor communications. Given the structural similarities of other capital equipment providers such as Tetra Pak, GEA, and Krones, the methodology is broadly replicable across the global F&B industrial equipment sector.

4. RESULTS AND DISCUSSIONS

The case study highlights several advantages of the proposed framework. First, it bridges the gap between operational and financial data by combining ERP-derived backlog information with CRM-derived opportunity data. This hybrid approach allowed the company to differentiate between stable backlog revenues and more volatile book-and-turn deals.

Second, the framework provided a structured channel for judgmental adjustments. While large deals were still subject to managerial review, these were explicitly separated from run-rate backlog items, reducing the scope for bias and over-optimism identified in previous studies (Fildes et al., 2009; Goodwin, 2010).

Third, the explicit inclusion of GAAP categories enhanced compliance and transparency. Previous forecasts often overstated equipment shipments while neglecting deferred or service revenues, creating mismatches between forecasted and reported figures. By aligning forecasts with IFRS 15/ASC 606 recognition rules, the framework ensured consistency between operational expectations and financial statements (PwC, 2021).

Finally, the improvement in forecast accuracy (from 85% to 92%) is particularly significant in high-value industries where even small deviations can translate into millions of dollars in investor guidance adjustments. As Moritz (2014) argues, global sales forecasting requires not only data sophistication but also frameworks tailored to industry-specific dynamics. This study provides a replicable template for industrial equipment providers facing similar challenges.

5. CONCLUSION

This paper introduced a structured forecasting framework for B2B capital equipment industries, with a particular focus on food and beverage manufacturing equipment providers. The framework integrates four distinct revenue categories—backlog, in-month orders, accounting adjustments, and GAAP-compliant revenues—into a consolidated methodology that links both revenue and margin forecasts.

The originality of the framework lies in its ability to combine statistical analysis, managerial judgment, and accounting principles into a coherent model. By applying

this approach, the case study firm improved forecast accuracy from 85% to 92% during a tariff mitigation crisis, demonstrating its practical effectiveness.

The implications of this contribution extend beyond a single company or industry. Any B2B capital equipment provider—such as Tetra Pak, GEA, Krones, or similar OEMs—can adapt the framework to improve the reliability of forecasts, align internal planning with external financial reporting, and enhance stakeholder confidence in volatile environments.

Future research may explore integrating machine learning techniques into the framework, particularly to refine hit rate predictions in CRM data or to model backlog realization under varying macroeconomic conditions. Nevertheless, the core contribution of this study is to demonstrate that structured, category-based forecasting can materially improve accuracy and strategic decision-making in industries where traditional statistical models fall short.

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