Partial Pooling for Improved Forecast Accuracy in Complex Industrial Time Series

Law Chew Sang*, Kenneth Chin, Lee Kin Kuan, Mohammad Shahbaz Hussain, Nur Syafrina Shahib, Adam Zaini, Abhishek Singh, Meenakshi Mishra, Peng Xu

ExxonMobil
22777 Springwoods Village Parkway
Spring, TX 77389

{chewsang.law, kenneth.c.weiyow, leekinkuan, mohammad.s.hussain, nur.s.shahib, adam.b.mohdzaini, abhishek.singh2, meenakshi.mishra1, peng.xu}@exxonmobil.com

Abstract

Demand forecasting in the chemical supply chain is essential for anticipating customer needs, managing inventory, and aligning production and distribution. However, traditional methods often fall short due to the industry's complexity. Popular time series forecasting techniques, when used as-is, often fail to deliver the desired accuracy, whether because of high model variance or limited data availability. To address this, we developed a *partial pooling* approach that leverages information from similar predictive tasks. Our results show that partial pooling achieved the highest forecast performance among popular statistical and machine learning models, even in industrial settings using relatively simple models. Moreover, partial pooling supports model sustainability by delivering strong performance with fewer models and reduced variance. It also facilitates faster experimentation and retraining, enabling quicker adaptation to changing market conditions.

Introduction

Demand forecasting in the chemical supply chain is a critical process that enables companies to anticipate customer needs, optimize inventory, and align production and distribution strategies. Given the industry's complexity, characterized by volatile raw material prices, diverse product portfolios, and globalized operations, traditional forecasting methods often fall short. Advanced techniques, particularly those leveraging machine learning (ML), have emerged as transformative tools. These models can process large datasets, identify patterns, and adapt to dynamic market conditions, significantly improving forecast accuracy and operational efficiency (Douaioui et al. 2024, Kannegiesser 2008, Gerhardues 2024). These advancements have opened new possibilities for improving forecasting in complex domains like the chemical industry. However, applying them effectively requires careful consideration of the unique characteristics and constraints of real-world operations.

In this paper, we seek to identify novel machine learning approaches that can improve demand forecasting in an industrial setting for chemical supply chain. We show that utilization of the SKU structure using partial pooling helps make better forecasts than other leading machine learning approaches.

Research on demand forecasting in the chemical industry remains relatively limited (Gerhardues 2024). (Bundgaard-Nielsen 1972) emphasized the importance of regression models for predicting chemical demand and pricing during the 1970s. (Broeren, Saygin, and Patel 2014) expanded the scope by identifying environmental factors influencing chemical consumption. More recently, (Estrada et al. 2020) explored various performance metrics for forecasting within the chemical sector, offering valuable insights into model evaluation and applicability. Comparative studies from forecasting competitions have highlighted the evolution of forecasting methods over time. The first competition, M1, focused solely on statistical models such as Holt's trend model (Holt 2004) and Winters' trend-seasonal model (Winters 1960), and the ARIMA model (Box 2013, Makridakis and

Hibon 1979). The second competition, M2, introduced judgmental forecasting (Makridakis et al. 1993). By the third competition (Makridakis, Ord, and Hibon 2000), more variations of these models were tested. The fourth competition marked the inclusion of machine learning (ML) models, which showed promise though did not outperform traditional methods. According to (Ni et al. 2020), ML adoption has grown significantly, a trend confirmed in the fifth competition (Makridakis, Spiliotis, and Assimakopoulos 2020), where ML models outperformed statistical ones.

Data for the chemical industry additionally often exhibits sporadic behavior where there are multiple demand peaks and intermediate periods of no (or less) demand exist. According to (Williams 1984), there are four types of demand patterns, which are smooth, intermittent, erratic and lumpy (refer to 3.0 methodology). This classification of demand patterns is made using the Coefficient of Variation (COV) and Average Demand Interval (ADI). ADI measures the regularity of demand over time by calculating the average interval between non-zero demand occurrences, while COV quantifies the variability in demand quantities. Numerous studies have been done in forecasting sporadic nature of chemical supply chain (Gamberini et al. 2010, Adur Kannan et al. 2020, Nikolopoulos et al. 2016).

The classification of demand patterns is a great method to handle variations in the demands of different industrial products. However, this method is not able to capture the relationship that exists between the demand of same products across different regions or the demand of similar products globally.

The concept of combining multiple individual forecasts has long been observed to often provide better forecast accuracy than a single forecasting model. The concept was popularized by the work of Bates and Granger (1969) and further established over time as a means to improve forecast accuracy as shown by Clemen (1989). Most recently, Makridakis (2022) reported that the results of the M5 *"Accuracy"* competition further supports the idea of combining forecast of different methods to improve forecast accuracy (Makridakis, Spiliotis, and Assimakopoulos 2022).

Taking a simple average, i.e., equal weights, of the combinations has been observed to be difficult to outperform compared to more complicated methods such as weighted averages (Wang et al. 2023). Using the simple average of multiple base models is observed through the popularity of bagging models in machine learning such as Random Forest. Furthermore, the winner, runner-up, and second runner-up of the M5 *"Accuracy"* competition all used an equal-weighted combination of forecast (Makridakis, Spiliotis, and Assimakopoulos 2022), further supporting the efficacy of taking a simple average of a combination of forecast.

A partial pooling strategy is a form of combination forecast that consists of creating multiple data pools that are found by grouping data samples based on their attributes. The extremities of a pooling strategy are complete pooling and no pooling. Complete pooling creates a single pool of data consisting of all data samples. A single model is then created for this single pool. In the context of demand forecasting, no pooling creates data pools at the bottom level of a hierarchical stock keeping unit (SKU) structure. A single model is then created for each SKU in the lowest level of the hierarchy.

Partial pooling offers a middle ground. Forecasting models are created for each group of data samples, resulting in multiple forecasts for a single SKU. The forecasts are then averaged with equal weightage to generate a final forecast for each SKU. This strategy allows shared learning while preserving group specific nuances. This attribute makes the partial pooling strategy suitable for data with a hierarchical or multi-level structure as observed in our problem.

Recent literature highlights its usefulness in retail and supply chain contexts, where forecasting across multiple products or regions benefits from capturing both global patterns and local variations (Oliveira and Ramos 2023). Pooling demand data across entities has also been shown to improve forecasting performance compared to isolated local models, as it leverages shared information to reduce noise and enhance generalization (Colby 2002). Similarly, demand forecasting using the partial pooling strategy for data with a hierarchical structure has proven to be useful for such purposes as shown by In (2022), who won the M5 *"Accuracy"* competition using a partial pooling strategy. Broader reviews on inventory pooling support its role in optimizing inventory levels and improving service rates, reinforcing its value in real-world supply chain applications (Yilmaz 2025). These findings suggest that partial pooling provides a scalable, efficient, and accurate approach to demand forecasting in complex supply chain environments.

In this paper, we optimize Univariate Forecasting Method, Multivariate Forecasting Method, Multivariate Ensemble Model with Demand Profiling, and Partial Pooling Method for the four demand patterns on real industrial data and implement the best performing method in production system for real decision making. We hypothesize that partial pooling can help with improving forecasting for all four demand patterns, smooth, intermittent, erratic and lumpy since it encourages transferring learning from similar groups. Hence, for demand patterns with sparse data, information sharing helps make better forecasts. Also, the simplicity of this method and the fact it needs fewer models will help in commercialization of this method for longer run in our experiment but multivariate ensemble models with demand profiling can be a good candidate too as it helps catering different methods to each demand pattern.

Application Description

In the chemical supply chain, there are several products and their grades that may be supplied from different locations. An SKU (Stock Keeping Unit) is a unique identifier used to track and forecast demand for a specific product configuration within the supply chain. Figure 1 shows the key attributes of SKU in our application and the hierarchy:

- **Plant**: The manufacturing or supply location responsible for producing or shipping the product.
- **Global Grade Pack ID (GGP ID)**: Represents the standardized product grade and packaging configuration used globally.
- **Region**: The destination region or market cluster where the product is delivered or consumed.

Together, these elements form a unique SKU that reflects both the product characteristics and the logistics footprint.

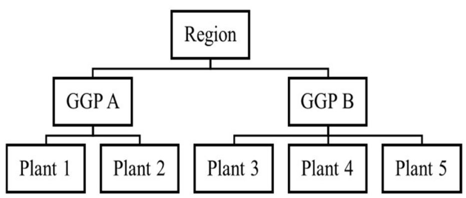

Figure 1: SKU-level granularity enables precise forecasting, planning, and inventory optimization across business units.

The demand forecasting problem we address involves generating monthly forecasts for each SKU over a six-month horizon, from M+1 (the next month) to M+6 (six months ahead). Since actual customer demand data is not available, we approximate demand using each SKU's historical shipment records.

These forecasts serve as critical inputs for supply, production, and replenishment planning. Forecast accuracy directly affects two key outcomes: working capital and service levels. A robust and accurate forecasting solution is essential for reducing uncertainty and enabling better decisions in inventory and supply planning.

Methodology

Our hypothesis is that partial pooling is a natural approach for leveraging the inherent structure of product hierarchies and supply chain networks. To evaluate its effectiveness, we compare it against three alternative methods: the traditional univariate method, the multivariate method, and the multivariate ensemble model with demand profiling.

To address the challenge of SKUs with limited historical data, we also introduce a Naïve model. This model is used consistently across all four approaches, including partial pooling, to ensure fair comparison and to handle low-data scenarios effectively.

Naïve Model

Before applying any advanced forecasting methods, we perform a preprocessing step to assess whether each SKU has sufficient historical data. SKUs with fewer than six non-zero shipment records, are considered to have insufficient data. These SKUs are handled using a Naïve model, which assigns future demand based on the average shipment volume over the last six months.

The Naïve model offers two key benefits. First, it enables efficient experimentation by quickly processing the large number of SKUs with limited data. Second, it prevents these low-data SKUs from introducing noise into the training of more sophisticated models, thereby preserving model quality and stability.

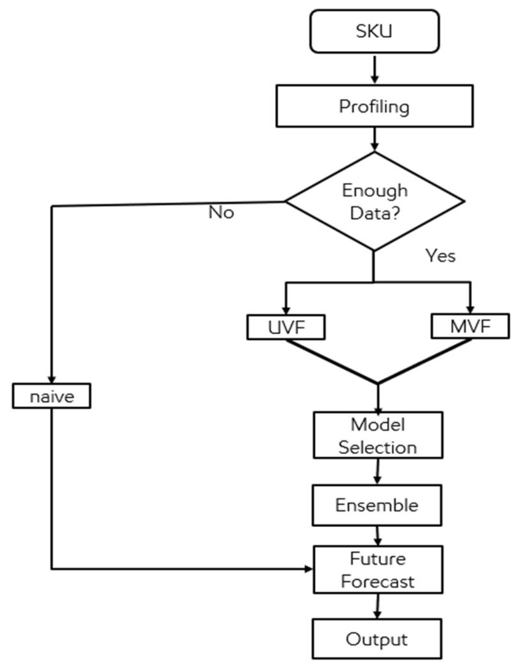

Figure 2: Multivariate method architecture.

The Naïve model applied in this paper is six-month simple average only with exception for Multivariate Model with Data Profiling (MMDP) which is ensemble of six-month simple average and Exponential Smoothing with trend.

Univariate Forecasting Method (UVF)

The univariate approach uses each SKU's historical shipment records to forecast its future demand independently. We trained several models under this framework, including moving average, simple exponential smoothing, Croston's method, ARIMA, and the fittest ARIMA. Each model is trained separately for each SKU.

For forecasting, we evaluate the performance of each trained model against a designated test period. Models that consistently over- or under-forecast where forecasts are higher or lower than 50% of actual value for six consecutive months are excluded from the final ensemble. The forecasts from the remaining models are then averaged to produce the final prediction.

Multivariate Forecasting Method (MVF)

The multivariate method combines both univariate and multivariate models to improve forecast accuracy. The univariate models used include Prophet, Holt-Winters, exponential smoothing, and ARIMA. Each univariate model is trained using the historical shipment records of individual SKUs.

In contrast, the multivariate models incorporate not only each SKU's historical data but also a set of external drivers, such as:

- Changes in consumer preferences
- Shifts in market trends
- Changes in economic conditions

These drivers were identified through collaboration with the demand planning team, data scientists, and the sales team. Features derived from these drivers include *lag values*, *log differences*, *rolling averages*, and *volatility*. To select the most relevant inputs, we applied a sequential feature selection algorithm. This method efficiently identifies combinations of features that work well together and captures both linear and nonlinear effects. The multivariate models used in our approach include Random Forest and Elastic Net.

For SKUs with sufficient data, forecasts are generated using both univariate and multivariate models. The top-performing models are selected based on their accuracy over the most recent three months. The final forecast is produced by averaging the outputs of these selected models. Figure 2 illustrates the architecture of the multivariate method.

Figure 2: Multivariate method architecture; UVF models include Prophet, Holt-Winters, exponential smoothing, and ARIMA.

Multivariate Model with Data Profiling (MMDP)

In this method, we begin by classifying SKU data based on forecastability, which is characterized by two statistical coefficients: Average Demand Interval (ADI) and Coefficient of Variation (COV). ADI measures the regularity of demand over time and is defined in Equation (1), while COV captures the variability in demand quantities and is defined in Equation (2).

$$ADI = \frac{total\ number\ of\ periods}{Number\ of\ periods\ with\ nonzero} \quad (1)$$

$$COV = \frac{standard\ deviation\ of\ demand}{total\ demand} \quad (2)$$

Demand profiles are classified based on the value of ADI and the squared COV (CV^2) as *smooth*, *intermittent*, *erratic* and *lumpy* with the following thresholds:

- *Smooth*: (ADI < 1.32, CV^2 < 0.49)
- *Intermittent*: (ADI >= 1.32, CV^2 < 0.49)
- *Erratic*: (ADI < 1.32, CV^2 >=0.49)
- *Lumpy*: (ADI>=1.32, CV^2>=0.49)

SKUs with sufficient data will be classified into one of these four profiles. For each profile, the multivariate method described above is used to forecast future demand. Figure 3 depicts the details of the architecture of this method.

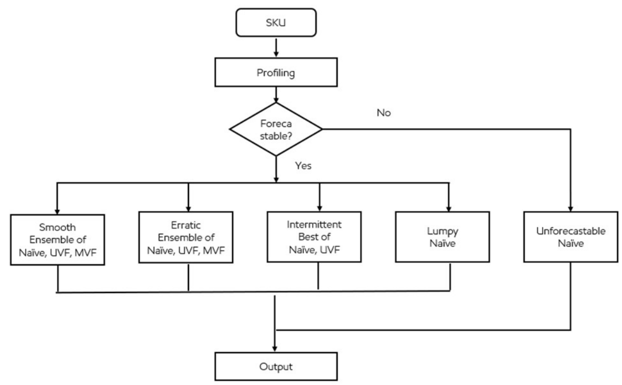

Figure 3: Architecture for multivariate model with demand profiling.

Partial Pooling Method (PPM)

The first step of the partial pooling is profiling followed by determination of whether an SKU is forecastable. The criteria for forecastability are defined as:

- Sufficient historical demand data
- Stable or predictable demand patterns
- Low levels of noise or missing data
- Consistent availability (not frequently out of stock).

For forecastable SKUs, the following features are exracted:

- Static features: ggp_id, country, location, super_region, product_group, product_sub_group.
- Lag features
- Rolling means of 3, 6, 9, 12 periods
- Rolling standard deviations of 3, 6, 9, 12 periods
- Seasonality features: year, half year, quarter, month

After this step, SKUs are grouped into hierarchical pools to enable cross-learning. These pools are 1. Global pool, 2.

Region pool, 3. Location pool, 4. Product group pool and 5. Product sub-group pool. These pools are defined by business domain knowledge. Global pool contains all SKUs across all regions and categories, Region pool refers to geographical zones such as Asia Pacific, Location pool refers to Country or market-specific grouping, Product pool contains SKUs of same high level product categorization and Product Sub-Group pool refers to more granular product segmentation.

By pooling SKUs in this manner, the model can cross-learn shared patterns, which may not be obvious for a single SKUs, especially for those will low volumes. LightGBM model is used due to its fast-training speed, high efficiency, and state-of-the-art performance. It is particularly well-suited for large datasets and provides excellent accuracy. The objective function is set to the Tweedie distribution as it effectively models the shipment volume data, which includes a mix of zeros and continuous positive values. This allows the model to handle both zero-inflated and right-skewed demand patterns. The model employed a recursive forecasting strategy, where predictions from previous time steps are fed back as inputs to generate forecasts for the subsequent time steps, capturing temporal dependencies over the forecast horizon.

The final step of the partial pooling method is to ensemble and the output from each pool's LightGBM model; in this case, the ensemble is a simple average.

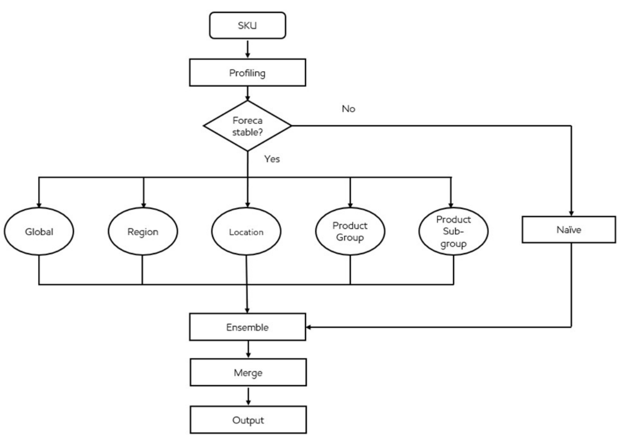

Figure 4: Detailed architecture of partial pooling method.

Experiments

Data and metrics

Our experiments include 3,000 SKUs with monthly shipment history records spanning from August 2020 to October 2023, which are used to train the models. For each SKU, we apply an expanding window approach across four folds to support training, validation, and model selection. A separate dataset, covering the period from September 2023 to February 2024, is used to evaluate model performance.

We assess each method using two metrics: weighted mean absolute percentage error (wMAPE) and forecast bias. These metrics are selected because they are directly used in business operations and have real-world implications. wMAPE helps improve customer service levels and reduce order break-ins, while forecast bias supports inventory optimization and working capital reduction. See Equations (3) and (4) for the calculation of wMAPE and bias.

$$wMAPE\ (\%) = \frac{\sum_{i=1}^{n} |forecast_i - actual_i|}{\sum_{i=1}^{n} actual_i} \times 100\% \quad (3)$$

$$Bias\ (\%) = \frac{\sum_{i=1}^{n} forecast_i - actual_i}{\sum_{i=1}^{n} actual_i} \times 100\% \quad (4)$$

These metrics are aggregated in two ways to reflect different business needs. *M1* refers to the forecast performance for the immediate next month (M+1), which is critical for short-term planning and responsiveness. *Overall* represents the average performance across the full six-month forecast horizon (M+1 to M+6), providing insight into longer-term planning effectiveness.

Results

Table 1 presents the forecast performance comparison across the four methods. The results show that the multivariate models perform similarly to the univariate method. In contrast, the multivariate model with demand profiling and the partial pooling approach achieves the lowest wMAPE at M+1.

Metric	UVF	MVF	MMDP	PPM
wMAPE (M1)	50.9	50.9	39.2	38.6
wMAPE (Overall)	51.9	51.9	41.7	41.7
FB (M1)	3.4	3.4	-5.0	-3.9
FB (Overall)	1.5	1.5	-5.5	-3.5

Table 1: wMAPE and bias comparison, where FB is forecast bias.

In terms of forecast bias (FB), both the univariate and multivariate models exhibit a positive bias. The multivariate model with demand profiling significantly reduces bias, while partial pooling offers the most balanced performance across both metrics and time horizons. These findings highlight the advantage of partial pooling and demand profiling in improving overall forecast quality.

	UVF	MVF	MMDP	PPM
# of Models	3000	12000	12000	5
Run time (hr)	1	1.5	2.5	0.3

Table 2: Number of models and runtime comparison.

Table 2 presents a comparison of the number of models and runtime across the four forecasting methods. The partial pooling approach stands out for its efficiency, requiring only five models to maintain. It also runs significantly faster than the other methods, making it highly practical for real-world applications where scalability and maintainability are critical.

Discussion

Multivariate method shows similar performance to the univariate method, suggesting that the external drivers may not significantly enhance forecast accuracy. One key reason is that many external drivers are updated quarterly or even annually, while the forecast operates at a monthly level. Additionally, these drivers often suffer from data quality issues, making them unreliable inputs. The higher dimensionality of the feature space further degrades the performance of some multivariate models, especially when the signal-to-noise ratio is low.

In contrast, the multivariate model with demand profiling demonstrates notable improvements in both forecast accuracy and bias. Profiling time series data using ADI and COV before forecasting provides a meaningful advantage, particularly in domains like supply chain and retail demand planning. This approach enables forecasters to apply specialized models tailored to the characteristics of each demand profile, rather than relying on a one-size-fits-all method that may underperform on irregular or sparse data.

The performance of partial pooling is comparable to that of the multivariate model with demand profiling. One possible explanation lies in the fundamentally different nature of these two approaches. Partial pooling emphasizes generalization, while demand profiling focuses on specialization to improve accuracy.

Generalization refers to a model's ability to perform well across a wide range of time series or scenarios. These models are typically trained on diverse datasets and aim to capture broad patterns that apply across multiple SKUs, making them scalable and efficient for large-scale forecasting tasks. However, they may underperform on time series with unique or highly localized behaviors.

In contrast, specialized models are tailored to the characteristics of a particular time series or cluster. This often results in higher accuracy for those specific cases but comes at the cost of flexibility and increased resource requirements. The trade-off between generalization and specialization is crucial: generalized models offer robustness and simplicity, while specialized models provide precision but require more effort to maintain and scale.

Another explanation for the similar performance could be a presence of a forecast ceiling. This refers to the upper limit of predictive accuracy that can be achieved, regardless of the modeling strategy, due to inherent data limitations. These limitations include low data quality, insufficient historical records, missing values, and a lack of informative external variables. The ceiling effect is particularly evident in domains with sparse, noisy, or highly volatile time series, where the signal-to-noise ratio is low. In such cases, improvements in modeling yield diminishing returns, and forecast accuracy plateaus due to the constraints of the input data. For this dataset, no theoretical approach is taken to prove the presence of forecast ceiling. However, empirically, order of 50-100 different modeling strategies was tested with no improvement in performance gains. This indicated a possibility of forecast ceiling.

Despite these challenges, partial pooling stands out as the most practical and scalable solution for deployed demand forecasting applications. While it delivers competitive forecast accuracy and bias, it significantly outperforms other methods in terms of operational efficiency. It requires only five model versions, compared to 3,000–12,000 in other approaches, drastically reducing the burden of model management and version control.

Additionally, partial pooling supports faster experimentation cycles with the shortest total runtime, making it ideal for agile environments where rapid iteration and scalability are critical. These advantages make partial pooling not only accurate but also highly efficient and sustainable for real-world forecasting systems.

Future Work

While developing the partial pooling approach, we grouped the data based on our best understanding of the product categories and supply chain network. However, there are various ways to pool data. In future work, we aim to evaluate the effectiveness of alternative pooling strategies.

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