Proceedings of the 2025 Winter Simulation Conference
E. Azar, A. Djanatliev, A. Harper, C. Kogler, V. Ramamohan, A. Anagnostou, and S. J. E. Taylor, eds.

AN EMPIRICAL STUDY ON THE ASSESSMENT OF DEMAND FORECASTING RELIABILITY FOR FABLESS SEMICONDUCTOR COMPANIES

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ABSTRACT

Fabless semiconductor companies—semiconductor design experts without their factories—serve as the essential bridge between sophisticated customer needs and technological innovations, playing a pivotal role in the semiconductor supply chain. At these companies, planning teams receive demand forecasts from the sales team and develop production plans that consider inventory, capacity, and lead time. However, due to the inherent characteristics of the semiconductor industry—high demand volatility, short product cycles, and extended lead times—a substantial gap often exists between sales forecasts and actual demand. Consequently, evaluating forecast reliability is critical for planning teams that rely solely on sales forecasts for production planning. In this paper, we propose a novel machine learning framework that assesses forecast reliability by classifying demand forecasts as either overestimates or underestimates rather than using regression methods. Experimental results confirm its effectiveness in assessing forecast reliability.

1 INTRODUCTION

Fabless semiconductor companies play a critical role in the semiconductor supply chain. These companies focus on chip design and research and development (R&D), operating without manufacturing facilities. They outsource wafer fabrication (front-end) and packaging and testing (back-end) to specialized foundries or outsourced semiconductor assembly and test (OSAT) providers. This business model enables them to avoid massive capital expenditures and mitigate operational risks while preserving their innovative design capabilities and market agility (Shin et al. 2017). In the semiconductor ecosystem, fabless firms are a vital bridge between technological innovation and market demand (Macher et al. 2007).

The semiconductor manufacturing process, from wafer fabrication to packaging and testing, involves complex, time-intensive steps. In particular, front-end processing can take several months. Consequently, fabless companies must place orders with foundries well in advance, considering the lengthy turnaround time (TAT) to satisfy future customer demand (Syberg et al. 2023). As illustrated in Figure 1, sales teams aggregate data from global branches and customers, leveraging their domain insight to produce demand forecasts. These forecasts are subsequently communicated to the planning teams responsible for placing orders at the foundry.

However, in this highly volatile and capital-intensive industry, forecasting errors impose significant risks across the semiconductor supply chain (Chopra and Meindl 2001; Uzsoy et al. 2018). Overestimating demand results in surplus inventory, increased storage costs, and potential depreciation of value, while underestimating demand leads to supply constraints, lost sales, and weakened market positioning (Zheng et al. 2018). Hence, precise demand forecasting is essential for effective production planning in fabless semiconductor companies.

Various demand forecasting methodologies have been explored in the semiconductor industry, ranging from traditional ARIMA models (Wang and Chen 2019) to diffusion models (Chen and Chien 2018;

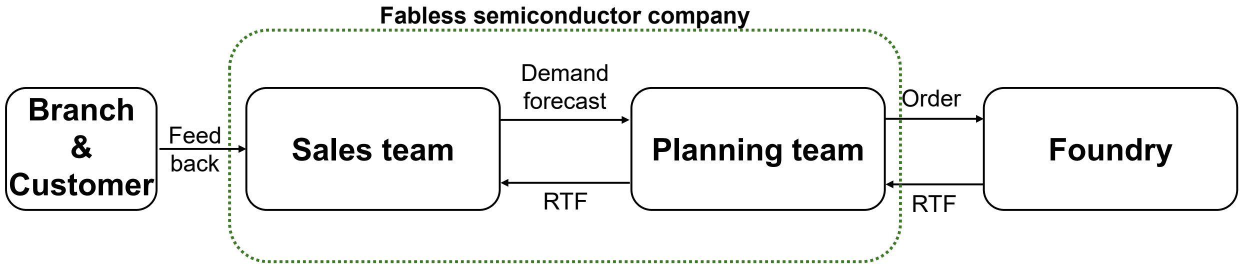

Figure 1: Decision-making process for semiconductor production orders in a Fabless semiconductor company. Return to Forecast (RTF) denotes the available supply quantity.

Chien et al. 2010) and ensemble forecasting methods (Xu and Sharma 2017). Recent innovations have employed machine learning (ML) approaches for demand forecasting with significant improvements in prediction accuracy (Fu and Chien 2019) and integrated frameworks combining multiple techniques for capacity planning optimization (Chien et al. 2024). Furthermore, advanced ML techniques, including deep reinforcement learning (Chien et al. 2020), have shown promising results in addressing the complex and dynamic nature of semiconductor demand.

These approaches have primarily focused on directly predicting demand values. However, given the practical decision-making processes in fabless companies, a framework is required to evaluate the reliability of sales team demand forecasts. Sales teams tend to overestimate demand due to optimistic targets and incentive systems, while customers often request surplus inventory to cover potential usage (Chang and Yen 2017), resulting in inflated forecasts provided to planning teams. This optimistic bias significantly undermines forecast accuracy, as positive adjustments to statistical forecasts are less effective and misdirected (Fildes et al. 2009). Therefore, assessing the reliability of demand forecasts ensures forecast accuracy through effective interdepartmental communication, enhances the overall planning process, and strengthens business performance (Syntetos et al. 2016).

In this paper, we introduce a novel ML-based framework that evaluates forecast reliability by classifying error magnitudes between the sales team forecast and actual demand rather than employing traditional regression methods. By leveraging historical actual demand data alongside current sales team forecasts, our model determines whether the demand forecast is overestimated or underestimated. Although previous research in demand forecasting has primarily used classification tools only to categorize product groups for selecting regression models (Pinçe et al. 2021), it has not been applied to assess the accuracy of sales team predictions. Our approach represents a novel application of classification techniques in demand forecasting for the semiconductor industry. To validate our classification model, we conducted an empirical study on a leading global fabless semiconductor company that must meet worldwide customer demand across a range of products. Considering the TAT in semiconductor manufacturing, our experiments were conducted to assess forecast reliability before placing orders with foundries. The experimental results demonstrate that our proposed framework achieved high classification accuracy across diverse products, underscoring its precise and robust capability in evaluating the reliability of demand forecasts.

The remaining paper is organized as follows: Section 2 introduces our classification framework; Section 3 presents the experimental design and results; and Section 4 provides the conclusion and outlines future research directions.

2 METHOD

This study proposes a decision-making framework to assess the reliability of the demand forecast provided by the sales team. Following the UNISON decision framework (Chien et al. 2020), we systematically define and address the problem. As shown in Figure 2, the UNISON framework consists of six steps:

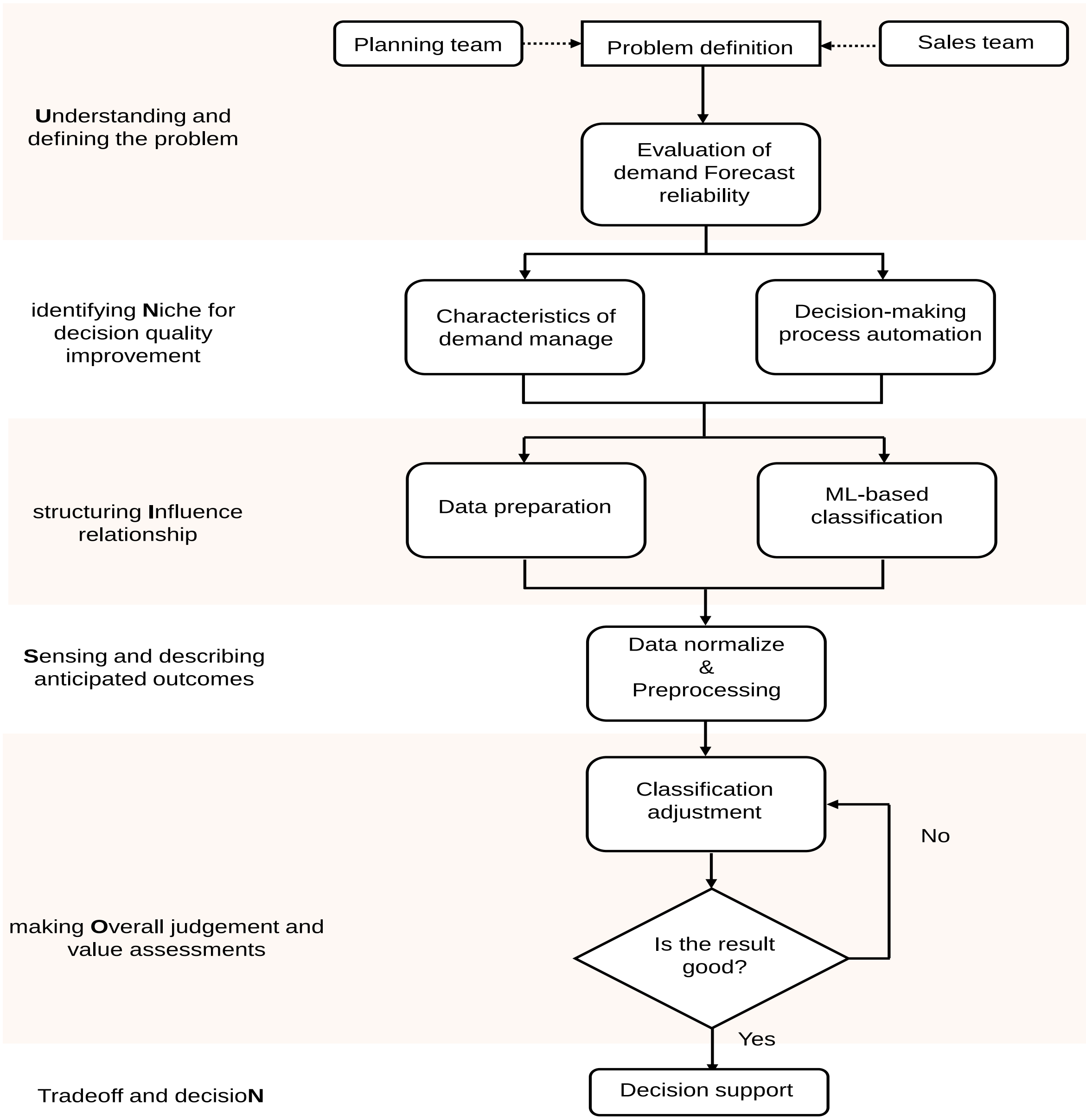

Figure 2: UNISON framework for evaluation of demand forecast reliability.

(1) understanding and defining the problem, (2) identifying a niche for decision quality improvement, (3) structuring influence relationships, (4) sensing and describing anticipated outcomes, (5) making overall judgments and value assessments, and (6) trading off and making a decision.

2.1 Understanding and defining the problem

In fabless semiconductor companies, the planning team must place orders to foundries appropriately to meet worldwide customer demands. Due to the absence of in-house manufacturing facilities and the resulting inflexibility in production operations, orders must be placed before the TAT. However, significant fluctuations in semiconductor demand and a TAT spanning several months render accurate order placement extremely challenging. Orders exceeding actual demand lead to high inventory costs, whereas orders that

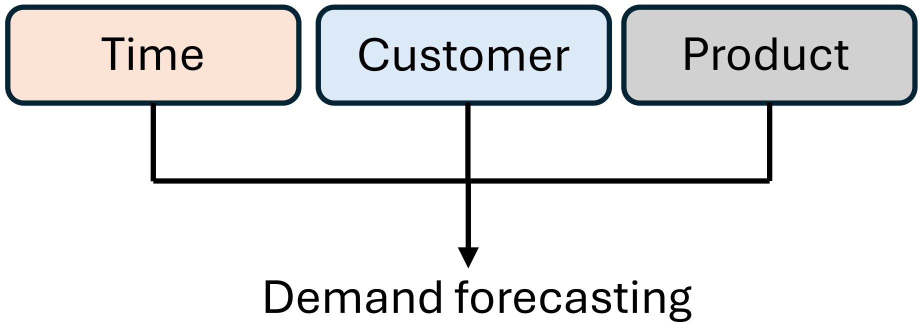

Figure 3: 3-dimensional demand management.

fall short result in stock shortages. Since these orders are based on sales team forecasts, establishing a framework to evaluate the validity of this information is crucial. Consequently, planning teams require a robust and precise method to assess the reliability of demand forecasts.

2.2 Identifying niche for decision quality improvement

Prior studies have primarily focused on determining the required quantity of a given product at a specific time. However, as illustrated in Figure 3, practical scenarios necessitate a three-dimensional demand management approach considering which customer requires which product and quantity at a given time. Consequently, the number of cases to manage becomes vast and complex, rendering manual management by field engineers impractical and labor-intensive. Furthermore, the variability in expert knowledge complicates unified decision-making. This challenge naturally motivates the automation of the decision-making process through machine learning, building on its recent success in production planning (González Rodríguez et al. 2020). In this context, our objective is to automate the reliability assessment of demand forecasts using machine learning and to enhance decision quality by integrating expert domain knowledge, ultimately improving overall business efficiency.

2.3 Structuring influence relationships

Based on the previously defined problem and identified opportunities, we prepare the data and build an automated model. We use historical actual demand data $\{d_{t-w},\ldots,d_{t-1}\}$, where w denotes the window size, and the demand forecast $\hat{d_{t|k}}$ at time t for time $t+k$. Specifically, assuming that at time t, we evaluate the forecast reliability for time $t+k$, we use the demand data from time $t-w$ to $t-1$ and the forecast $\hat{d_{t|k}}$ for time $t+k$ received from the sales team at time t, to assess whether $\hat{d}_t$ is overestimated. Therefore, $X=\{d_{t-w},\ldots,d_{t-1},\hat{d_{t|k}}\}$ is treated as a single data instance. Relying solely on historical demand data reflects that most companies have not developed sufficient data collection capabilities or integrated information systems needed for comprehensive, multifaceted analyses. The data is generated using a sliding window method, as illustrated in Figure 4. It is noteworthy that the sliding method for data generation is applied after the data is split into training and testing sets.

We approach our problem not as a regression task that predicts real values but rather as a classification task that categorizes the magnitude of forecast errors. Solving this classification problem requires predefined classes to organize the data. Accordingly, we propose two classification tasks: a binary classification task to determine whether demand is overestimated or underestimated and a multi-class classification task to evaluate the extent of overestimation when it occurs. The rationale for focusing solely on overestimation in the multi-class task stems from business priorities to minimize excessive inventory resulting from inflated forecasts.

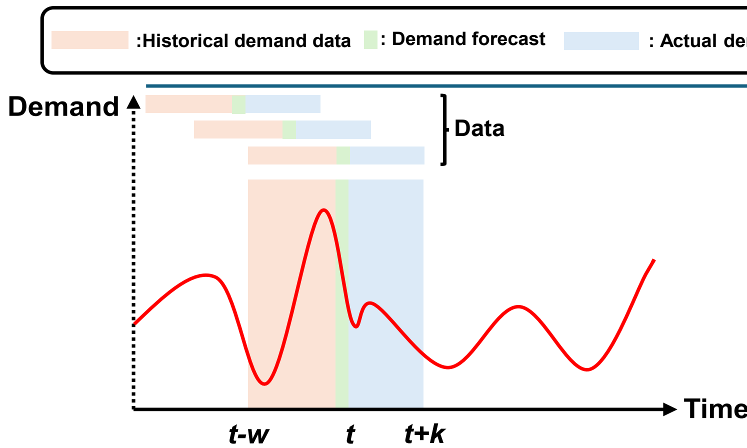

Figure 4: Data generation using the sliding window method.

Finally, we apply multiple machine learning models, each leveraging their distinct strengths, to address the classification problem. These models have been widely employed in existing production planning literature (Chien et al. 2020).

- **K-Nearest Neighbor (K-NN)**:
  K-NN is a machine learning algorithm that classifies data by considering the labels of the k nearest neighbors.

- **XGBoost**:
  XGBoost (Chen and Guestrin 2016) is an ensemble learning-based algorithm that builds on the gradient boosting framework. It sequentially fits new decision tree models using gradient information to correct the shortcomings of previous models and linearly combines them while employing techniques to prevent overfitting.

- **Multi Layer Perceptron (MLP)**:
  MLP is an artificial neural network composed of multiple layers of perceptrons. It is effective in processing nonlinear data (Adhikari 2015).

- **Long Short Term Memory (LSTM)**:
  LSTM (Hochreiter and Schmidhuber 1997) is a variant of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data.

2.4 Sensing and describing anticipated outcomes

Our objective is to develop a unified model applicable to all products and customers. However, given the varying demand scales across the three dimensions of demand management, appropriate data preprocessing is essential. To capture scale-independent patterns, we normalize the data values using the Min-Max normalization technique, as shown in the equation 1 (Patro and Sahu 2015).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Furthermore, to enhance data quality and optimize our model's performance, we employed a variety of data preprocessing techniques, including data gathering, cleaning, and reformatting. These processes involve extracting historical demand records from the database, removing duplicate or irrelevant entries, and consolidating the information.

2.5 Making overall judgments and value assessments

To evaluate the classification performance of our framework, we employ both accuracy and F1-score metrics. While accuracy is the most straightforward measure for classification models, it often falls short when dealing with imbalanced class distributions. To address this limitation, we also utilize the F1-score, which considers precision (the proportion of correctly identified overestimations among all predicted overestimations) and recall (the proportion of correctly identified overestimations among all actual overestimations). The F1-score is computed as the harmonic mean of precision and recall, as follows:

$$F1-score = \frac{2 \times Precision \times Recall}{Precision + Recall}. \tag{2}$$

2.6 Trade off and decision

Finally, the proposed model enables the planning team to make holistic decisions by integrating their domain knowledge with the outputs of the classification model. Close collaboration with the sales team, they can fine-tune demand forecasts and place more precise orders with the foundry, thereby establishing a more stable semiconductor supply chain, enhancing business efficiency, and reducing costs.

3 EMPIRICAL STUDY

3.1 Problem definition and structuring

Focusing on the practical needs of a leading fabless semiconductor company in Asia, we conducted an empirical study to assess the validity of the proposed framework. In particular, the case company is a global leader in semiconductor manufacturing, supplying a diverse array of products to various customers worldwide. As a result, there is a critical need to meet global demand flexibly. In this context, once the sales team issues demand forecasts, the planning team must evaluate the reliability before placing orders with the foundry. Motivated by the need for a robust and practical framework for demand forecast validation, we developed a machine learning-based model that makes decisions based on historical demand data and the demand forecasts provided at the time of decision-making.

3.2 Data

We collected monthly historical demand and forecast data for 210 products spanning a total of 37 months from the database. Although aggregating data monthly reduces the sample size, the case study company prioritized monthly forecasts over weekly ones, thus providing monthly demand data. A TAT (k) of 3 months was assumed, and the window size was fixed at 8 months. Note that not all products had demand data throughout the entire collection period due to the semiconductor industry's short product cycles, resulting in a few products being sold continuously for three years. Therefore, maintaining a long window size for all product groups was challenging. For the same reason, preliminary analysis found no evidence of seasonal and cyclical demand patterns in our dataset. The data cannot be disclosed publicly due to contractual obligations with the case study company.

We conducted two experiments: The first identified whether the demand forecast was overestimated, and the second assessed the degree of overestimation when it occurred. Labels were assigned by comparing forecasted values with actual demand. Specifically, forecasting error (%) was defined as $100 \times (\hat{d_{t|k}} - d_{t+k})/d_{t+k}$, where d_{t+k} denotes the actual demand at time $t+k$. Labels corresponding to different error magnitudes were established based on business requirements. The first experiment (Class A) is a binary

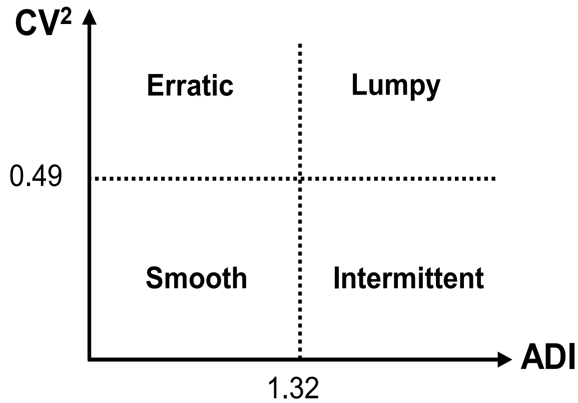

Figure 5: Demand pattern classification. CV^2 denotes the coefficient of demand variation and ADI represent inter-demand intervals.

classification task designed to evaluate whether demand forecasts are overestimated or underestimated. Accordingly, the classes are defined as follows:

- **Class A (binary)**:
  class 1: $< 0\%$, class 2: $0\% >$.
  The percentage indicates the degree of forecast error.

The second experiment comprises a binary and a multiclass classification task designed to evaluate the degree of overestimation. The rationale for conducting this experiment is based on the realistic need to address the fact that overestimation, which can lead to excessive inventory accumulation, poses a greater risk than underestimation. In consideration of class balance and practical requirements, the classes are divided as follows:

- **Class type B (multiclass)**:
  class 1: $0\% \sim 29\%$, class 2: $30\% \sim 99\%$, class 3: $100\% <$.

- **Class type C (binary)**:
  class 1: $0\% \sim 99\%$, class 2: $100\% <$.

While some studies, as illustrated in Figure 5, categorized demand patterns using classification rules (Syntetos et al. 2005) and built distinct models for each pattern (Chien et al. 2020), our analysis revealed that most of our data exhibit a lumpy pattern (high demand variance and long demand interval). Thus, we adopted a unified model rather than constructing separate models for each pattern. For model training and testing, 70% of the dataset was used for training, 15% for validation, and the remaining 15% for testing.

3.3 Model hyperparameter

To optimize the hyperparameters for each machine learning model, we employed a greedy search, with the final configurations presented in Table 1. Notably, early stopping was applied at 50 epochs for every task.

Table 1: Hyperparameters for different classification tasks.

Method	Parameter	Task type Class A	Class B	Class C
K-NN	n_neighbor	7	7	7
	metric	manhattan	euclidean	manhattan
XGBoost	max_depth	3	5	3
	learning rate	0.01	0.01	0.01
	n_estimators	100	100	100
MLP	hidden layer size	16	16	(8,16)
	activation function	ReLU	ReLU	ReLU
	learning rate	0.005	0.0001	0.005
	Optimizer	Adam	Adam	Adam
	Training epoch	1000	5000	10000
	Batch size	64	64	64
LSTM	hidden layer size	16	30	16
	learning rate	0.0001	0.0001	0.0001
	Optimizer	Adam	Adam	Adam
	Training epoch	1000	5000	1000
	Batch size	64	64	64

Table 2: Performance evaluation results of different models on Class A.

Model	Accuracy	F1-score
K-NN	0.8214	0.8207
XGBoost	0.5357	0.5363
MLP	**0.8929**	**0.8930**
LSTM	0.7857	0.7835

3.4 Experimental results

We evaluated the performance of machine learning models on real-world data. As previously discussed, our experiments involved k-NN, XGBoost, MLP, and LSTM, with accuracy and F1-score as evaluation metrics. The highest accuracy and F1-score are highlighted in bold.

Table 2 showed the evaluation results of the first experiment. The XGBoost model performed poorly in classification, whereas the MLP model achieved nearly 90% accuracy and F1-score, demonstrating robust and efficient performance in assessing demand forecast reliability. Notably, the MLP outperformed the LSTM, a model generally more adept at handling sequential data. This may be attributed to the

Table 3: Performance evaluation results of different models on Class B and Class C.

	Model	Accuracy	F1-score
Class B	K-NN	0.6000	0.6710
	XGBoost	**0.8000**	**0.7981**
	MLP	0.5333	0.5386
	LSTM	0.5333	0.3710
Class C	K-NN	0.7333	0.7333
	XGBoost	0.6000	0.5889
	MLP	**0.8000**	**0.8000**
	LSTM	0.6000	0.5400

data's intermittent nature, high variability, and relatively short window size, which hinder the extraction of meaningful sequence patterns.

Table 3 showed the evaluation results of the second experiment. The XGBoost model demonstrated good performance on Class B with an accuracy and F1-score. The MLP model performed well on Class C tasks but yielded lower metrics on Class B. The K-NN model demonstrated relative consistency between class types with moderate performance metrics. These results suggested that different model architectures had varying strengths depending on the specific classification task, which could have potentially informed future work on targeted model selection or ensemble approaches. While no single model excelled across all scenarios, these findings provided valuable insights into the relative capabilities of these algorithms on our specific dataset.

4 CONCLUSION

In this study, we propose a novel machine learning-based framework designed to rigorously assess the reliability of demand forecasts, specifically addressing critical operational challenges faced by the production planning team of a leading global fabless semiconductor company in Asia. Due to industry characteristics, the company must place manufacturing orders with external foundries significantly in advance, relying entirely on the accuracy of sales forecasts provided by its sales team. Consequently, developing a robust method to evaluate the validity and reliability of these forecasts is crucial. To this end, we reframe forecast evaluation as a classification problem rather than a traditional regression task. Our proposed method employs a purely data-driven approach to categorize forecasting errors into distinct classes based on their magnitude, leveraging historical demand records and the corresponding forecasts available at the time orders are placed. This approach closely mirrors the practical and operational decision-making processes inherent to semiconductor production planning. Empirical analysis conducted using real-world datasets demonstrates the robustness and efficacy of our machine learning models, highlighting their practical utility in improving decision-making quality through enhanced forecast reliability assessment.

Despite the demonstrated effectiveness of our framework, our approach has several potential limitations. First, our current approach depends solely on historical actual demand and forecast data due to restricted data availability. Integrating additional internal and external market data such as customer type, product category, and inventory could enable the consideration of broader factors. Second, although we focused on a case study from a leading fabless company in Asia, the effectiveness of our framework has been validated only on a specific dataset; therefore, further validation across diverse datasets is required. Finally, our experimental results indicate that the best-performing ML algorithm is problem-dependent, highlighting the potential for developing an adaptive system that can select the most effective model according to the context, potentially utilizing reinforcement learning, supervised learning, or large language models.

ACKNOWLEDGMENTS

This work was supported by System LSI, Samsung Electronics.

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