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# Investigating the Potential of Machine Learning and Deep Learning Models in Probabilistic Supply Risk Forecasting: A Case Study in the Automotive Sector

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**Abstract:** In recent years, the growing number of disruptions across industries has driven researchers to explore the potential of artificial intelligence tools in proactively predicting supply chain risks. A key area of focus has been the use of machine learning and deep learning algorithms to predict supplier punctuality, particularly given the importance of anticipating late deliveries for companies that implement just-in-time or lean manufacturing strategies. However, existing studies have primarily examined the ability of these tools to make deterministic predictions, leaving a gap in understanding their capacity to provide probabilistic predictions in this domain. This paper addresses this gap through a case study investigation in the automotive sector, where the performance of traditional, machine learning, and deep learning models in making probabilistic predictions have been compared. Specifically, accuracy metrics such as coverage probability, sharpness, and interval score have been computed for the different class of models in the examined case study for short term and long-term forecasting horizons. Additionally, the models were assessed in terms of training time and storage requirements, providing a comprehensive comparison of their practical implementation.



*Keywords:* Supply chain management, supply chain resilience, supply chain risk management, artificial intelligence, machine learning

## 1. INTRODUCTION

In today's interconnected global marketplace, anticipating supply chain risks has become vital for organizations aiming to maintain a competitive edge and operational resilience. Increasing costs and delays are straining supply chains, significantly impacting production plans. According to McKinsey & Company, (2023), companies may face disruptions capable of erasing half a year's profits or more over the next decade, where a single prolonged shock can wipe out 30% to 50% of annual earnings before interest, taxes, and depreciation for many sectors, particularly in agriculture, automotive, and energy. To mitigate these risks, adopting Artificial Intelligence (AI) has emerged as a promising solution. Numerous studies have highlighted the tangible benefits of integrating AI in supply chain management (Culot et al., 2024; Pournader et al., 2021) to enhance resilience and risk management practices (Baryannis et al., 2018; Ivanov & Dolgui, 2020; Kassa et al., 2023). Among AI technologies, Machine Learning (ML) and Deep Learning (DL), due to their predictive capabilities, have demonstrated to be helpful in anticipating changes in demand (Gabellini et al., 2022), detecting supply risks (Gabellini, Calabrese, et al., 2023, 2024) and to be able to support typical supply chain decision-making problems (Regattieri et al., 2024). In particular, recently, considerable attention has been put into understanding the potential of ML and DL algorithms in solving the problem of predicting supplier delivery punctuality. Indeed, in a context characterized by just-in-time and lean manufacturing practices, punctual deliveries from suppliers represent a fundamental prerequisite to guarantee smooth production flows. To this end, early studies have thus started to approach the problem in binary form by evaluating the capabilities of ML and DL to estimate if a future supplier would have been delivered late or not (Baryannis et al., 2019; Brintrup et al., 2020; Cavalcante et al., 2019). Subsequentially, studies have started to approach the problem in regression form, trying to predict the exact amount of delays related to each delivery (Barros et al., 2023; Steinberg et al., 2023). Lastly, recent works have focused on improving the existing model's accuracy by examining the benefits of extending data collection with data from third-party data providers (Bodendorf et al., 2023; Gabellini, Civolani, et al., 2024) or by considering data from other industries through privacy-preserving mechanisms (Zheng et al., 2023). However, despite these promising findings, existing studies predominantly focused on examining ML and DL algorithms' capability to generate only deterministic predictions of supplier delivery punctuality. Therefore, as emerges from Table 1, which summarizes the main studies related to the problem, a notable lack of research investigating the potential of ML and DL models in generating probabilistic forecasts related to supplier


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delivery punctuality is lacking. However, probabilistic forecasting is particularly valuable in supply chains, where uncertainties and variability are inherent, and decisions need to be taken considering these aspects. Based on this evidence, this study thus aims to fill for the first time the existing lack of studies investigating the capability of ML and DL models to provide probabilistic forecasts of supplier delivery punctuality. To address this gap, data from a real automotive case study were collected, and a comparative experimental design has been designed to address the following research questions (RQ):

RQ 1. Are ML and DL models more suitable than traditional statistical models for generating probabilistic forecasts of supplier delivery punctuality?

RQ 2. How do ML and DL models compare with traditional methods in terms of the computational cost required to generate probabilistic forecasts of supplier delivery punctuality?

The structure of this paper thus proceeds as follows: Section 2 will present the case study and the experiments designed to investigate the RQs. Section 3 will outline the results. Lastly, Section 4 will discuss the results and conclude by offering insights and recommendations for practitioners and suggestions for future research.

Table 1. Summary of literature related to supplier delivery delay prediction

| Study | ML task | Forecast type | Case study | Evaluation criteria |
|---|---|---|---|---|
| (Cavalcante et al., 2019) | C | D | Synthetic data | ROC, Accuracy, |
| (Baryannis et al., 2019) | C | D | Maritme sector | MCC, Acc, Rec, $F_1$, Prec |
| (Brintrup et al., 2020) | C | D | Complex asset manufacturer | Prec, Rec, F-score |
| (Steinberg et al., 2023) | R | D | German machinery industry | MAE, RMSE, $R^2$, |
| (Bodendorf et al., 2023) | C | D | Automotive sector | Acc, AUC, Recall, F-score |
| (Barros et al., 2023) | R | D | Bosch automotive electronics | MAE, MSE, RMSE, $R^2$, sME, sMSE, |
| (Zheng et al., 2023) | C | D | Maritme engineering sector | Acc, Prec, Rec, F-score |
| (Gabellini, Civolani, et al., 2024) | R | D | Automotive sector | MAE, RMSE, SMAPE |
| This study | R | P | Automotive sector | Coverage probability, Sharpness, Interval Score, |

R: Regression, C: Classification, D: Deterministic, P: Probabilistic, Prec: Precision, Rec: Recall, AUC: Area Under Curve, MCC: Matthews Correlation Coefficient, ROC: Receiver Operating Characteristic curve, MAE: Mean Absolute Error, RMSE: Root Mean Squared Error, SMAPE: Symmetric Mean Absolute Percentage Error, sME: scaled Mean Error, $R^2$: R-squared, sMSE: scaled Mean Squared Error

## 2. MATERIALS AND METHOD

The investigated case study is presented in the following Section, and a detailed description of the experiments conducted to investigate the RQs described in Section 1 is presented.

### *2.1 Case study*

The case study investigation involved an Italian automotive company. The company was selected as the automotive sector represents a critical sector characterized by high complexity and reliance on timely supplier deliveries. To investigate the RQs introduced in Section 1, a comprehensive data collection of the historical evolution of its supplier delivery punctuality has been performed. The metadata of the collected dataset has been reported in Table 2. Here, the number of different supplier country locations has been computed considering the NUTS standard for country classification (European Commission, 2021), while the number of different supplier sectors involved has been computed considering the NACE standard for sector classification (European Commission, 2008).

Table 2. Dataset meta data

| Metadata | Value |
|---|---|
| N° of different supplier country locations | 2 |
| N° of suppliers | 30 |
| N° of different supplier sectors involved | 10 |
| N° of components | 122 |
| Time period | 2020-10-21 to 2024-04-24 |
| N° samples | 11’755 |

A classification of the patterns of the collected time series according to the classification introduced in Syntetos et al., (2005) is instead reported in Table 3.

Table 3. Dataset time series classification

| Time series classification | % of time series |
|---|---|
| Smooth | 4,9 % |
| Erratic | 95,1 % |
| Intermittent | 0 % |
| Lumpy | 0 % |

Lastly, the distribution of collected supplier delivery punctuality data is reported in Table 4.

Table 4. Dataset target value distribution

| Statistic | Value [days] |
|---|---|
| Mean value | 7.1 |
| Standard deviation | 27.2 |
| Min value | -26 |
| Q1 | -4.0 |
| Q2 | 1.0 |
| Q3 | 13.0 |
| Max value | 44 |

### 2.2 Experimental design

A comparative analysis of various models was conducted across three distinct classes: statistical methods, ML methods, and DL methods, to investigate the value of ML and DL models in generating probabilistic predictions of supplier delivery punctuality in the examined case study. Each class included two representative models, thereby facilitating an assessment of their performance in forecasting supplier delivery punctuality. The Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing State Space Models (ETS) were selected in the statistical methods category. These models represented established benchmarks in time series forecasting and provided a basis for evaluating traditional statistical approaches. The Prophet algorithm was utilized within the ML category, known for its capacity to account for seasonality and holiday effects in time series data. Additionally, CatBoost, a gradient-boosting model adept at handling categorical variables, was incorporated into the analysis. For the DL class, Long Short-Term Memory (LSTM) networks were employed, which are designed to capture long-term dependencies in sequential data. Additionally, NHiTS was utilized to represent state-of-the-art architecture for time series forecasting that leverages hierarchical modeling. The predictive capability of all models was compared in their univariate forms, meaning that only historical data was used as input to generate predictions. This approach aimed to isolate the intrinsic forecasting abilities of each model without the influence of additional covariates. Moreover, the models were trained under two different paradigms. ETS and ARIMA and Prophet, were developed as local models to serve as individual forecasts for each time series as this was its only training possibility for them. In contrast, CatBoost, LSTM networks, and NHiTS, were trained as global models to provide a singular predictive framework for all-time series. Global training indeed represents the typical training strategy for ML and DL models. The evaluation metrics adopted to assess the performance of these models in generating probabilistic forecasts included the Coverage Probability (CP), the Sharpness (S) and the Interval Score (IS). CP refers to the proportion of times the true value falls within the predicted interval. S measures the width of the prediction intervals, with a sharper (narrower) interval indicating higher precision. The IS combines sharpness and coverage, penalizing wide intervals and those failing to contain the true value, aiming for an optimal trade-off between accuracy and precision. A higher coverage indicates more accurate uncertainty estimation. Additionally, the training time in seconds and the storage space in MegaByte has been monitored. The CP has been computed according to Equation 1:

$$CP = \frac{1}{N}\sum I(L_t \leq y_t \leq U_t) \tag{1}$$

The Sharpness has been computed according to Equation 2:

$$S = \frac{1}{N}\sum(U_t - L_t) \tag{2}$$

The IS has been computed according to Equation 3:

$$IS = (U_t - L_t) + 2 * \max(0, L_t - y_t) + 2 * \max(0, y_t - U_t) \tag{3}$$

In the previous Equations, $N$ represents the number of timestep in the test set, $L_t$ represents the lower bound predicted at time t, $U_t$ represents the upper bound predicted at time t, $y_t$ represent the true value of the target variable at time t.

### 2.3 Experimental setup

For each forecasting model, the dataset was initially split into three distinct subsets: the training set (from 2020-10-21 to 2021-12-31), the validation set (from 2021-12-31 to 2022-12-31), and the test set (from 2022-12-31 to 2024-04-24), ensuring that the temporal integrity of the dataset was maintained throughout the modeling process. The training dataset was utilized to initially train each model, allowing the algorithms to learn from historical patterns and relationships within the data. Following the training phase, the validation dataset was employed to fine-tune the hyperparameters of each model within a time limit of 8 hours. The tuning process aimed to identify the optimal hyperparameter configuration that maximized the IS value on the validation set, thereby enhancing the predictive performance of the models. The hyperparameter research space explored and those selected for each model are summarized in Table 5:

Table 5. Hyperparameter research space and selected value for the investigated probabilistic models

| Model | Hyperparameter | | |
|---|---|---|---|
| | **Name** | **Space** | **Selected** |
| Prophet | Seasonality mode | Addit., Multipl. | Multipl. |
| | Changepoint prior scale | [0.001, 0.5], | 0.11 |
| | Seasonality prior scale | [0.001, 10.0], | 6.66 |
| | Holidays prior scale | [0.001, 10.0], | 6.00 |
| | N changepoints | [5, 50], | 7 |
| | Changepoint range | [0.5, 0.95], | 0.54 |
| | Interval width | [0.5, 0.95], | 0.92 |
| CatBoost | Lags | [1:200] | 93 |
| | Iterations | [100:2000] | 308 |
| | Learning rate | [0.01:0.3] | 0.015 |
| | Depth | [3:10] | 4 |
| | L2_leaf_reg | [1:10] | 4.18 |
| | Likelihood | 'quantile' | |
| | Quantiles | 0.25 - 0.5 - 0.75 | |
| LSTM | Input chunk length | [1:48] | 26 |
| | Hidden dim | [5:100] | 9 |
| | N rnn layers | [1:5] | 1 |

| | | | |
|---|---|---|---|
| | Dropout | [0.0:0.5] | 0.31 |
| | Training length | [12:72] | 23 |
| | N epochs | [1:100] | 73 |
| | Likelihood | Quantile regression | |
| NHits | Input chunk length | [1:48] | 28 |
| | Output chunk length | [1:24] | 11 |
| | Num stacks | [1: 5] | 1 |
| | Num blocks | [1:5] | 2 |
| | Num layers | [1:3] | 1 |
| | Layer widths | [32:512] | 451 |
| | Dropout | [0.0:0.5] | 0.015 |
| | activation | [ReLu,Tanh, LeakyReLu] | Tanh |
| | Max pool 1D | [True:False] | True |
| | N epochs | [1:100] | 76 |
| | likelihood | Quantile regression | |

Once the best hyperparameter configuration was selected for each model, the training and validation datasets were combined to retrain the models using the identified optimal hyperparameters. This approach aimed to maximize the models' learning capacity by utilizing all available data. Finally, the testing dataset was reserved for evaluating the performance of the retrained models. Specifically, the probabilistic predictions were generated considering a sample size equal to 100 samples for each model, and two different forecasting horizons were considered for the test set. The short-term forecasting horizon has been assumed to equal each component's lead time. Conversely, the long-term forecasting horizon spanned over a year. For both the forecasting horizon, the performance metrics, including CP, S, and IS, were computed using the test set. Additionally, the training time in seconds and storage space in megabytes were monitored during the training phase.

### 2.4 Computational setup

The computational experiments were conducted on a workstation with the following specifications: an Intel® Core™ i9-10900 CPU operating at 2.80 GHz, 64 GB of RAM. The workstation operated on Windows 10 Pro (version 22H2). The operating system was based on a 64-bit architecture. The experiments were implemented using Python, with the Optuna library employed to optimize hyperparameter tuning. Additionally, the Darts library was utilized to construct various forecasting models, enabling the implementation of ARIMA, ETS, Prophet, CatBoost, LSTM, and NHiTS models.

## 3.RESULTS

The distribution across the examined component time series of the different performance metrics for each model and for the two different forecasting horizons has been reported in Figure 1.

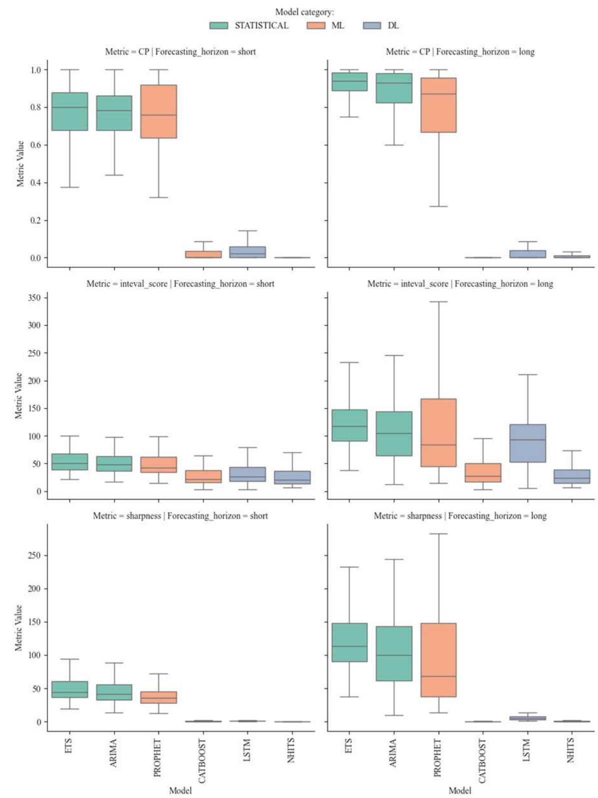


Figure 1. Performance error distribution across the examined time-series of the investigated probabilistic models

According to Figure 1, in short-term forecasting, statistical models and ML models trained locally exhibited the highest median CP, followed by ML models trained globally and DL models presenting the lowest median values. Regarding the interquartile width, statistical models displayed the widest distribution, indicating a higher variability in coverage probability. ML models followed, while DL models demonstrated the narrowest interquartile, reflecting the most consistent performance across the examined components' time series. DL models reported lower median error for sharpness, followed by ML models. Here, statistical models recorded instead the highest median values. In terms of variability, models reported similar performances. Lastly, concerning the IS, DL models demonstrated the lowest median error value, with ML models in the middle and statistical models presenting the highest. Similarly, the interquartile width of the interval score was widest for statistical models, indicating greater variability, followed by ML models. DL models again showed the narrowest interquartile, highlighting their more consistent interval score performance. In long-term forecasting, patterns similar to those observed in short-term forecasting can be observed in Figure 1. However, the highest value for the CP, S, and IS can be noticed when considering statistical and ML models. On the contrary, the value of the CP, S, and IS for DL models remain similar to those reported in the short-term forecasts.
Figure 2 reports instead the percentage of components for which a specific model reported the best performance separately for the two-forecast horizon.

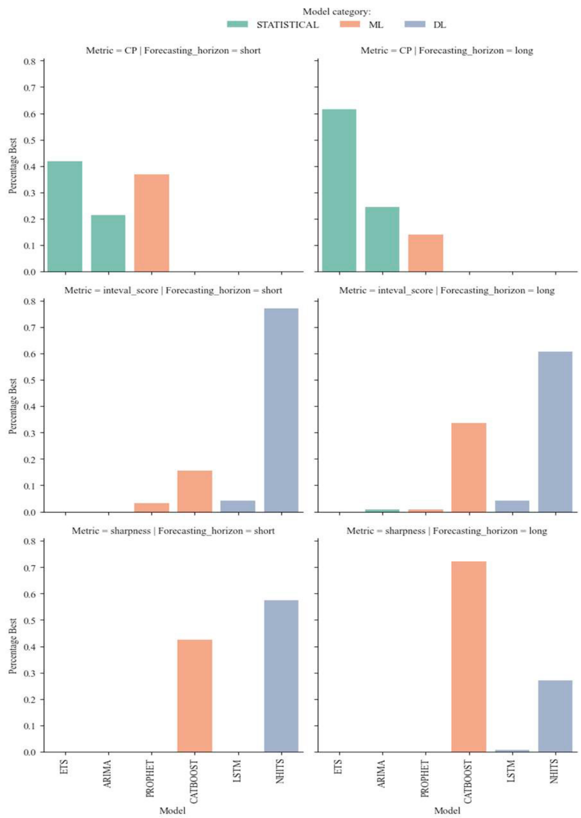


Figure 2. Percentage of time series for which the analyzed probabilistic forecasting models result as the one with the best performance error

According to the charts, statistical and ML models trained locally resulted in the best results for most components when considering the CP metrics. On the contrary, ML and DL models performed better for most components in terms of S and IS metrics. No significant changes have been reported when moving from a short-term to a long-term forecasting horizon. Lastly, the training time and the storage space for each model independently on the considered forecasting horizon have been instead reported in Table 6.

Table 6. Training time [s] and storage space [MB] required of the analyzed probabilistic models

| Model Classification | Model name | Training time [s] | Storage space [MB] |
|---|---|---|---|
| Statistical | ARIMA | 24,5 | 4,4 |
| Statistical | ETS | 1,8 | 5,9 |
| ML | Prophet | 153,1 | 68,1 |
| ML | CatBoost | 8.87 | 0,33 |
| DL | LSTM | 2543,3 | 0,01 |
| DL | NHits | 1713,1 | 0,01 |

According to the table, DL models resulted in the one requiring the lowest storage space, followed by the statistical and ML models. Considering the training time instead on opposite situations has been noticed with DL, resulting the one requiring the longer training time, followed by ML models and lastly by statistical models

## 4. DISCUSSION & CONCLUSIONS

Accurate predictions of supplier delivery punctuality have become vital for industries seeking to avoid shortages and stockouts. While AI, particularly ML and DL, has been explored for generating deterministic forecasting in this problem, there is limited focus on their use in probabilistic forecasting. This study addressed this gap by examining the potential of ML and DL models for probabilistic forecasts in the automotive sector compared to traditional methods. Using case study data, we designed experiments to evaluate ETS, ARIMA, Prophet, CatBoost, LSTM, and NHits models in terms of probabilistic metrics such as coverage probability, sharpness, and interval score metrics. Training time and storage requirements were also analyzed to assess trade-offs. Results for RQ1 revealed that ML and DL models better-balanced coverage probability and sharpness, as indicated by superior interval scores. However, the training strategy covers a relevant role, as evident from the difference in the results of ML models trained globally and those trained locally. For RQ2, DL models had the longest training times, followed by ML and traditional models. However, ML and DL models trained globally could be more efficient for large-scale time series than traditional methods, which require localized training. Practical implications emerged: ML and DL models, especially if trained globally, are better choices when balancing sharpness and coverage probability or when managing numerous components is required. Instead, traditional models excel in generating broader distributions and are faster for smaller datasets. Additionally, although a direct comparison with deterministic models for supply risk forecasting, such as those by Zheng et al. (2023) and Bodendorf et al. (2023), is not feasible due to the differences in the types of forecasts produced, the results indicate that the ML and DL models explored in this study offer a promising solution to reduce the key limitation of traditional models, namely the inability to estimate the level of uncertainty in predictions. This study needs, however, to be considered subject to limitations, including reliance on a single case study and univariate model forms. Future research should thus validate these findings across multiple case studies and can be potentially directed to investigate the effects of incorporating additional external data on probabilistic accuracy like those reported in Gabellini, Civolani, et al. (2023)

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