IBIMA Publishing
Communications of International Proceedings
https://ibimapublishing.com/p-articles/46AI/2025/4642625/
Vol. 2025 (34), Article ID 4642625

Comparative Analysis of Neural Network Architectures for Production Demand Forecasting*

Kamil MUSIAŁ [0000-0002-7615-7165], Artem BALASHOV [0000-0002-2937-1070],
Joanna KOCHAŃSKA [0000-0002-4695-1640] and Dagmara ŁAPCZYŃSKA [0000-0002-4745-0768]

Wroclaw University of Science and Technology, Wroclaw, Poland

Correspondence should be addressed to: Kamil MUSIAŁ, kamil.musial@pwr.edu.pl

* Presented at the 46th IBIMA International Conference, 26-27 November 2025, Ronda, Spain

Abstract

Forecasting production demand is one of the key elements of effective supply chain management in small and medium-sized enterprises. The paper presents a comparative analysis of different neural network architectures used in production demand forecasting. The study includes the evaluation of neural networks: unidirectional (MLP), recursive (RNN), long-term memory (LSTM), recursive units (GRU), convolutional networks (CNNs) and hybrid models combining multiple architectures. The analysis showed that the choice of the appropriate network architecture depends on the characteristics of the time data, the degree of complexity of demand patterns and the available computing resources. LSTM networks show high performance in modeling long-term time dependencies, while CNN-BiLSTM hybrid models offer the best results in the context of multivariate time series. The article provides recommendations for choosing optimal architectures for specific production scenarios.

Keywords: demand forecasting, neural networks, production management, deep learning

Introduction

Global competition is evolving rapidly, and dynamic changes in market conditions are making it increasingly challenging for manufacturing companies to effectively forecast demand. Small and medium-sized enterprises have limited resources, making accurate demand forecasts critical for optimizing inventory levels, capacity planning, and minimizing operating costs. Traditional forecasting methods, such as moving averages or ARIMA models, often prove insufficient to deal with the complex, non-linear demand patterns characteristic of modern markets (Chaudhuri et al., 2025; Aidoo-Anderson, 2025).

The digital transformation of processes creates new opportunities for the application of advanced forecasting techniques based on artificial intelligence. Neural networks have shown a high ability to capture complex patterns in time series and adapt to changing market conditions (Lim et al., 2021).

This article provides a systematic review and comparison of different neural network architectures in the context of production demand forecasting. In particular, it focuses on evaluating the practical usefulness of the selected architectures in terms of prediction accuracy, computational requirements, and data availability necessary to train the models.

Cite this Article as: Kamil MUSIAŁ, Artem BALASHOV, Joanna KOCHAŃSKA and Dagmara ŁAPCZYŃSKA, Vol. 2025 (34) “Comparative Analysis of Neural Network Architectures for Production Demand Forecasting " Communications of International Proceedings, Vol. 2025 (34), Article ID 4642625, https://doi.org/10.5171/2025.4642625

Literature Review and Research Context

Demand forecasting is a key component of a production planning system, and its accuracy has a direct impact on the efficiency of the entire supply chain (Chaudhuri et al., 2025; Aidoo-Anderson, 2025). Research has shown that companies using advanced forecasting methods achieve a reduction in forecast errors of up to 51% compared to traditional approaches, which translates into significant financial savings. For small businesses, where profit margins are often limited, neural network-based demand forecasting can determine market competitiveness (Areerakulkan, N. et al., 2024)

Traditional approaches to demand forecasting, based on statistical methods such as ARIMA or regression models, show significant limitations in volatile market conditions. These models assume the stationary nature of time series and may not be flexible enough to capture the rapidly changing demand patterns characteristic of modern markets.

Neural networks, through their ability to learn nonlinear relationships between input variables and the predicted variable, offer much greater flexibility. Compared to traditional models, neural networks show better adaptability to changes in market conditions and can process many input variables (temperature, seasonality, promotions, etc.) at the same time.

Neural Network Architectures for Demand Forecasting

Multilayer perceptronic networks (MLPs) are the oldest and simplest neural network architecture, consisting of an input, one or more hidden layers, and an output layer. Each neuron in the layer is connected to each neuron in the next layer, and the information flows in one direction - from input to output. When forecasting demand, MLPs work well for low-complexity issues. Research indicates that for data with clearly linear patterns, MLPs can achieve an average percentage absolute error (MAPE) of 8-11% (Toprak et al., 2025). Unfortunately, the main disadvantage of MLP is the lack of a built-in structure to handle time sequences - each time point is treated independently of the others, which leads to the loss of time dependency information.

Recursive networks, unlike MLPs, have feedback loops that allow the network to store information about previous inputs. The RNN architecture is naturally suited to time sequence processing, as each output is a function of not only the current input, but also the hidden state from the previous time step.

Traditional RNN networks, on the other hand, are characterized by a fading gradient problem, which makes it impossible to model long-term dependencies in time series. Regardless of this limitation, simple RNNs exhibit a MAPE of about 3.0% in cases where time dependencies are short-term and are not hindered by fading gradient problems (Ibrahim et al., 2023).

Long Short-Term Memory **(**LSTM) networks represent a significant improvement over traditional RNNs by introducing special "cells" capable of storing and recalling information over significant time frames. The LSTM architecture includes three types of gates: forget gate, input gate and output gate, which regulate the flow of information on the network.

In empirical studies, LSTM networks have shown a significant advantage over other architectures in forecasting production demand. For example, LSTM models achieved a MAPE of 1.5-2.5% when forecasting demand for both durable and non-durable products. LSTM's ability to capture long-term time relationships makes them particularly useful for time series with distinct seasonality and trend (Ibrahim et al., 2023).

The use of LSTM enables the implementation of more advanced business models such as made-on-demand manufacturing, where accurate forecasts of changing demand are crucial to optimize material flow and reduce inventory.

Gated Recursive Units (GRUs) are a simplified version of the LSTM architecture, retaining its key advantages in temporal dependency modeling. Instead of three gates, the GRU includes only two: a reset gate and an update gate, which reduces the number of parameters to train and reduces the risk of overlearning.

Comparative studies have shown that GRUs show similar performance to LSTM, and sometimes even slightly better on smaller datasets. For a specific example with air passenger demand forecasting, the two-layer GRU model achieved an RMSE of 22.47 and an IEA of 18.16, which was slightly better than the analogous LSTM model (Zachariah et al., 2023). The advantage of GRU lies in its lower computational requirements, which makes it attractive for enterprises with limited IT resources.

Convolutional networks (CNN), most commonly used in image processing, have found a foothold in time series forecasting. CNNs can be effective in extracting local patterns and features from time series through the use of convolutional filters.
For demand forecasting, CNNs are suitable for modelling rapidly changing - irregular demand patterns (so-called "intermittent demand"). The research demonstrates that CNN networks developed as two-class classifiers (to determine whether demand will be in a given period) in combination with another network to estimate the amount of demand, significantly outperform traditional models (Belmiro et la. (2024).

Hybrid models

Currently, hybrid models that combine the advantages of different neural architectures are becoming more and more popular in demand forecasting. Particularly popular are:

- **CNN-LSTM**: Convolutional networks extract spatial features from time series, and LSTM models long-term time relationships
- **CNN-BiLSTM**: An extension of the CNN-LSTM model by using bidirectional LSTM (Bidirectional LSTM) networks that can process time series both forward and backward.
- **Transformers with Attention Mechanism**: Recent approaches use transformers with an attentive mechanism that allow the model to dynamically allocate attention to different parts of historical data.

Comparing the performance of architectures

The following metrics were used to compare the performance of different architectures:

- **Mean Absolute Error (MAE):** Mean absolute error, expressed in units of original data

- **Root Mean Squared Error (RMSE):** root of the mean squared error, more sensitive to large deviations

- **Mean Absolute Percentage Error (MAPE): Mean Absolute Percentage Error (MAPE)** that allows you to compare accuracy between different time series

Based on a literature review and empirical research, the following architectures are the most promising for common production demand forecasting tasks:

- **MLP networks**: MAPE at 8-11%, suitable for simple, less variable time series
- **RNN**: MAPE about 3.0%, better than MLP, but limited by fading gradient problems
- **LSTM**: MAPE 1.5-2.5%, clear advantage in time and seasonality modeling
- **GRU:** MAPE 1.7-2.0%, close to LSTM, with lower computational requirements
- **CNN**: effective for irregular demand patterns, especially in demand attendance/absence classification
- **CNN-LSTM**: MAPE 1.2-1.8%, best results for multidimensional time series
- **Transformers**: showing promising results with a reduction in MSE error of up to 3.6% compared to previous approaches

It should be noted that the actual performance of any architecture depends on the characteristics of specific data and the tuning of hyperparameters.

Challenges and Limitations in Implementation

One of the key challenges in implementing neural networks for demand forecasting is the quality of the historical data available. For small businesses that may have limited ways of collecting and storing data, problems such as missing values, outliers, or a lack of sufficient data history can occur, which can significantly reduce the performance of models.

More advanced architectures, especially CNN-LSTM or Transformers, require significant computational resources. For small businesses with limited IT budgets, cheaper alternatives such as GRU, offering a better trade-off between performance and cost, are becoming promising.

Neural networks with a large number of parameters tend to overfit from training data, leading to poor quality results. To counteract overfitting, it is important to carefully select the size of the training set, use regularization techniques and cross-validation.

Summary and Conclusion

A comparative analysis of different neural network architectures has shown that there is no single best solution for forecasting production demand, and the choice of the appropriate architecture requires taking into account factors such as: data characteristics, available computing resources, size of the training set, or specific business requirements.
LSTM networks and their variants have proven to be consistently reliable solutions for most demand forecasting scenarios, offering a good balance between performance and complexity. For small businesses just entering their digital transformation, GRU models can provide a more practical alternative due to lower computational requirements.

The CNN-LSTM and CNN hybrid models show greater potential for future applications, for multivariate, complex time series. On the other hand, transformers with an attention mechanism are a promising direction for further research.

For small businesses implementing advanced business models, accurate demand forecasting is a key component of digital transformation success. Starting with GRU models, progressively moving to LSTM as technical capabilities increase, and possibly adopting hybrid models after gaining experience is a recommendation for the implementation of demand forecasting systems for small businesses.

References

- Aidoo-Anderson, A. (2024) "Investigating demand forecasting practices and challenges in Ghana's Manufacturing Pharmaceutical (MPharma) small and medium enterprises (SMEs): insights and recommendations", *International Journal of Production Research*.
- Areerakulkan, N., Moryadee, C., Trakoonsanti, L., Khaengkhan, M., Setthachotsombut, N. (2024), "A New Product's Demand Forecasting Using Artificial Neural Network", *College of Logistics and Supply Chain*, Suan Sunandha Rajabhat University, Dusit, Bangkok, Thailand.
- Belmiro, M. et al. (2024), "Graph Neural Networks in Intermittent Time-Series Forecasting", Proceedings of the International Conference on Neural Networks and Machine Learning (ICNNML 2024), Atlantis Press.
- Chaudhuri, A., Subramanian, N., Dora, M. (2022). "Circular economy and digital capabilities of SMEs for providing value to customers: Combined resource-based view and ambidexterity perspective". *Journal of Business Research*, 142, 32-44.
- Ibrahim, I.A. et al. (2023). "Short-term multivariate time series load data forecasting at the individual and aggregated level" *Energy*, 202, 118456.
- Lim, B., Zohren, S. (2021). "Time-series forecasting with deep learning: a survey", *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 379 (2194), 20200209.
- Toprak Fırat, A., Aygün, O., Göğebakan, M., Akay, M.F., Ulus, C. (2025). "Development of machine learning based demand forecasting models for the e-commerce sector". *Uluşlararası Mühendislik Tasarım ve Teknoloji Dergisi*, 7(1), 13–20.
- Zachariah, R.A., et al. (2023). "Systematic review of passenger demand forecasting in aviation industry." *Journal of Air Transport Management*, 109, 102447.