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# A Comparative Study of Deep Learning and Traditional Statistical Models for Demand Forecasting

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## Abstract

Demand forecasting underpins inventory, production and workforce planning, and the choice between traditional statistical models and neural approaches remains contested. This study compares five forecasters, namely a seasonal naive benchmark, Holt-Winters exponential smoothing, seasonal ARIMA, a two-hidden-layer neural network on lagged inputs, and gradient boosting on lagged inputs, in a controlled simulation of 12 weekly product-demand series spanning three years. The series embed annual and quarterly seasonality, trend, sporadic promotions and one of two noise levels, so that the effect of series smoothness on model ranking can be isolated. Over a 12-week horizon, ARIMA attains the lowest mean absolute percentage error (12.1%), with Holt-Winters and gradient boosting close behind (12.5%); the neural network trails (18.9%) and has the widest error dispersion. On smooth series the gradient-boosting model is best (8.2%), whereas on erratic series ARIMA is clearly best (16.5%). The findings reproduce, in a transparent setting, the pattern reported in large forecasting competitions: on short, individually modelled series, statistical methods remain highly competitive, and the benefit of learned models materialises only when the series are smooth enough to reward the richer feature representation. A decision guide for selecting forecasting methods by series characteristics is proposed.

**Keywords:** Demand forecasting; ARIMA; exponential smoothing; neural networks; gradient boosting; forecast accuracy.

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## Introduction

Every manufacturing, retail and service organisation forecasts demand, and the accuracy of those forecasts translates directly into inventory cost, stock-outs and service levels. Two families of methods compete for this task. Traditional statistical models, principally exponential smoothing and ARIMA, encode explicit assumptions about level, trend and seasonality and have been refined over decades [1], [2]. Deep learning models, including recurrent networks [3], global sequence models [4] and the architectures surveyed in [5], learn representations from data and have delivered impressive results on large pooled datasets.

The evidence on which family should be preferred in practice is mixed. The M4 competition found that pure machine-learning entries underperformed simple statistical benchmarks on the majority of series, while a hybrid of exponential smoothing and a recurrent network won overall [6]. An earlier comparison reported that statistical methods dominated machine-learning methods across a range of horizons [7]. At the same time, practitioners with large product portfolios report gains from learned models, particularly when exogenous drivers such as promotions are available.

A difficulty in interpreting this literature is that real demand datasets differ in length, seasonality, noise and the presence of exogenous shocks, so that comparisons across studies are confounded by data characteristics. This paper addresses the difficulty with a controlled simulation in which those characteristics are set by design. The questions are: (i) how do representative statistical and learned forecasters compare on short weekly series; (ii) how does series smoothness change the ranking; and (iii) what decision rule follows for method selection in a product portfolio?

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## Related Work

### Statistical forecasting

Exponential smoothing decomposes a series into level, trend and seasonal components updated recursively; the Holt-Winters variant handles additive seasonality and remains

a workhorse for operational forecasting [1]. ARIMA models represent a differenced series through autoregressive and moving-average terms, extended with seasonal terms for periodic data [2]. Both families are estimated per series and extrapolate structure rather than learning it from other series.

### Learned forecasting

Neural forecasting treats prediction as supervised learning on lagged windows. Feed-forward networks on lag vectors are the simplest instance; recurrent architectures such as long short-term memory [3] process the window sequentially; and global models such as DeepAR [4] and N-BEATS [8] are trained across many series, which allows them to learn shared seasonal and promotional patterns. Gradient boosting on lagged and calendar features [9] is widely used in retail because it handles exogenous variables and nonlinear interactions without sequence-specific architecture. Surveys [5] note that the advantage of learned models grows with data volume and shrinks on short series.

### Evaluation practice

Accuracy comparisons depend on the metric and the horizon. Mean absolute percentage error (MAPE) is intuitive for demand but undefined for zero demand; scaled errors avoid that problem [10]. Rolling-origin evaluation over multiple series and horizons is the recommended practice [1], and this study follows it in simplified form with a fixed origin and 12 series.

### Demand forecasting in operations management

Forecast accuracy matters because it propagates into inventory policy. Under a periodic-review policy, safety stock scales with the standard deviation of forecast error over the lead time, so a reduction in error from 15% to 12% of demand lowers the safety stock required for a given service level by roughly the same proportion. Conversely, a forecaster that performs worse than the seasonal naive benchmark, as can happen when a complex model is applied to short series, raises inventory cost while appearing sophisticated. The practical question for operations managers is therefore not which method is best in the abstract but which method is best for each class of series in their portfolio, and how to detect when a deployed method has stopped earning its keep.

## Methodology

### Synthetic demand series

Twelve weekly series of length $T = 156$ (three years) are generated. Series $k$ has base level $L_k \sim U(200, 800)$, linear trend with slope drawn from $U(-0.5, 1.5)$ units per week, annual seasonality of amplitude $0.20\,L_k$ and quarterly seasonality of amplitude $0.08\,L_k$, promotions occurring with probability 0.10 per week that add between 20% and 50% of base demand, and Gaussian noise with standard deviation equal to either 5% (smooth) or 15% (erratic) of the base level, assigned at random:

$$y_t = L + \delta\, t + 0.20\, L \sin(2\pi t/52) + 0.08\, L \sin(2\pi t/13) + \pi_t + \varepsilon_t,\quad \varepsilon_t \sim N(0, \sigma^2). \quad (1)$$

Negative values are truncated at zero. The last 12 weeks of each series form the test horizon; all models are fitted to the first 144 weeks.

### Forecasters

Five forecasters are compared. The seasonal naive forecast repeats the value from 52 weeks earlier. Holt-Winters exponential smoothing uses additive trend and additive seasonality with period 52. Seasonal ARIMA uses order (2,1,1) with a seasonal autoregressive term at lag 52. The neural network is a multilayer perceptron with hidden layers of 64 and 32 units trained on a window of 26 lagged values, the promotion indicator for the target week and a scaled time index; forecasts are produced recursively. Gradient boosting uses the same features. Statistical models are fitted with statsmodels and learned models with scikit-learn [11]. Hyperparameters are defaults, which places all methods on an equal, untuned footing.

### Metrics

Accuracy is measured by MAPE over the 12-week horizon, averaged across series. Results are also reported separately for smooth and erratic series.

### Experimental controls

Three controls keep the comparison fair. First, all methods receive exactly the same training window and are evaluated on exactly the same 12 test weeks for every series. Second, the learned models receive the promotion indicator for the target week, which mirrors the realistic situation in which promotion calendars are known in advance; the statistical models do not use it, so any advantage of the learned models partly reflects this information rather than the learning algorithm alone. Third, the random seed is fixed, so the series, the promotion schedule and the neural-network initialisation are identical across runs. The harness can be re-executed with different seeds to obtain sampling distributions of the metrics.

## Results

### Overall accuracy

Table 1 reports mean MAPE. ARIMA is best overall (12.07%), with Holt-Winters (12.52%) and gradient boosting (12.51%) essentially tied behind it. All three improve on the seasonal naive benchmark (14.99%). The neural network is the weakest forecaster (18.86%), worse than the naive benchmark, and Figure 1 shows that it also has by far the widest dispersion of errors across series, with a maximum MAPE above 40%.

**Table 1:** Mean absolute percentage error over the 12-week horizon (12 synthetic weekly series)

| *Forecaster* | *MAPE, all series (%)* | *MAPE, smooth series (%)* | *MAPE, erratic series (%)* |
|---|---|---|---|
| Seasonal naive | 14.99 | 11.39 | 22.18 |
| Holt-Winters (ETS) | 12.52 | 8.70 | 20.15 |
| Seasonal ARIMA | 12.07 | 9.85 | 16.51 |
| Neural network (lagged MLP) | 18.86 | 17.21 | 22.16 |
| Gradient boosting (lagged) | 12.51 | 8.24 | 21.06 |

### Effect of series smoothness

The ranking changes with noise. On smooth series, gradient boosting is best (8.24%), followed by Holt-Winters (8.70%) and ARIMA (9.85%); the learned model's ability to use the promotion indicator and to represent the two seasonal cycles jointly pays off when the signal-to-noise ratio is high. On erratic series, ARIMA is clearly best (16.51%), with every other method clustered between 20% and 22%; the parsimonious ARIMA specification is less prone to fitting noise than either the seasonal smoothing model or the learned models.

### Why the neural network underperforms

Three mechanisms explain the network's result. Each series contributes only 118 training windows, which is far too few for a model with several thousand parameters. The recursive forecasting scheme feeds the network's own errors back as inputs, compounding mistakes over the horizon. And the model has no built-in notion of seasonality beyond what it can infer from 26 lags, which is shorter than the annual cycle. Global training across series and architectures that encode seasonality explicitly address these issues [4], [8], and the result should be read as characterising per-series feed-forward networks rather than deep forecasting in general.

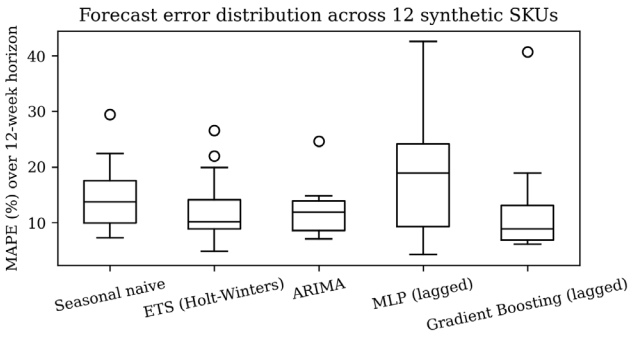



**Figure 1:** Distribution of 12-week MAPE across the 12 synthetic series by forecaster.

## Discussion

### Reconciling the evidence

The simulation reproduces the central finding of the forecasting competitions [6],[7] in a transparent setting: on short, individually modelled series, well-specified statistical models are hard to beat, and learned models win only where the data reward them. It also identifies the condition under which they do: smoothness, or equivalently a high signal-to-noise ratio, combined with informative exogenous features. This reconciles the competition results with practitioner reports of success in large retail portfolios, where series are aggregated to a level at which noise is modest and promotion calendars are available.

### A selection guide

The results support a simple portfolio rule. Classify each series by its noise level, estimated for instance from the residual coefficient of variation of a seasonal naive fit. For erratic series, deploy a parsimonious statistical model and focus improvement effort on aggregation and safety stock rather than on model complexity. For smooth series with exogenous drivers, deploy gradient boosting or a global neural model, and validate that the gain over Holt-Winters is material. For all series, retain the seasonal naive forecast as a monitoring benchmark; any model that falls below it, as the per-series network did here, should be withdrawn.

### Implications for forecasting practice

Organisations often adopt a single forecasting technology for an entire portfolio. The regime-dependence documented here argues for method diversity governed by series characteristics, which is also the logic of the hybrid approaches that performed best in the M4 competition [6]. It further argues for investing in the data that learned models need, namely clean promotion and calendar features and sufficient history, before investing in the models themselves.

### Monitoring deployed forecasters

A forecaster that was best at deployment can deteriorate as series characteristics change, for instance when a product matures and its demand becomes more erratic, or when promotional intensity changes. The selection guide therefore needs a monitoring loop: compute the rolling ratio of each model's error to the seasonal naive error, and re-run the selection rule when the ratio drifts above one or when the estimated noise class of the series changes. Because the statistical models are cheap to refit, they can serve as a standing fallback while the learned models are retrained.

## Limitations

The comparison is limited to twelve series, one origin and one horizon, and to untuned default configurations. The neural representative is a feed-forward network trained per series; recurrent and global architectures were not included and may perform differently. The data-generating process contains additive seasonality and Gaussian noise, which favours the additive statistical models. All figures are simulation outputs and should not be interpreted as estimates for any product category. Extending the harness to intermittent demand, multiplicative seasonality, pooled training and rolling origins is straightforward and would strengthen the conclusions.

## Conclusion

In a controlled comparison on short weekly demand series, seasonal ARIMA delivered the lowest overall error, Holt-Winters and gradient boosting were close competitors, and a per-series neural network was the weakest forecaster. Series smoothness determined the ranking: learned models excelled on smooth series with promotional drivers, while parsimonious statistical models excelled on erratic series. Rather than choosing between deep learning and statistics, organisations should classify their series and match methods to them, retaining simple benchmarks as a safeguard.

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