



Naïve Forecasting: A Tool to Compare Forecast Models

Chuda Prasad Dhakal¹ and Hari Bhakta Shahi²

¹Institute of Agriculture and Animal Sciences, Tribhuvan University, Kirtipur, Kathmandu, Nepal

²Tribhuvan University, Public Administration Campus, Kathmandu, Nepal

Email: ¹chuda.studies@gmail.com , ²haribhaktashahi7@gmail.com

Corresponding Author: Chuda Prasad Dhakal

Abstract: *In this study, a freshly fitted forecast model is put up against a standard procedure for comparison. But first, the essay makes a distinction between the confusing notion of a prediction model's accuracy measure and a comparison of forecast models in terms of gauging their relative and absolute accuracy measures in various scenarios. A forecast model's accuracy measure by itself does not give a complete picture of how much better a newly fitted model is than other benchmark models built from the same dataset.*

This article illustrates the comparison of a multiple regression model as a novel fit with the naive forecasting methodology, a well-known benchmark in the forecasting area, using cross-validation techniques. The performance of the forecast models was assessed using two generally used accuracy measures, Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). It was discovered that the multiple regression model performs better than the naive technique in both MAE and MAPE. This meant the multiple regression model was a worthy fit.

In summary, it is crucial to compare a newly developed forecast model with benchmark models to evaluate its performance accurately. This process allows for the identification of the most suitable forecasting method for a specific context and promotes the development of improved techniques for comparing forecast models in the future.

1. Introduction

Forecasting is a technique that utilizes historical data to estimate future trends (Tuovila, 2022). Different forecast models are developed through various approaches for the same purpose and data set (Chambers, Mulick, & Smith, 1971). The selection of a forecasting method depends on various factors, such as the context of the forecast, availability of historical data, degree of accuracy desired, and time period to forecast (Chambers et al., 1971). Forecast accuracy measures are essential for evaluating the performance of a forecasting model. There are various methods to measure the accuracy of a forecast, including

$$\text{Mean Forecast Error (MFE)} = \frac{\sum(A - F)}{n}, \quad (\text{Armstrong \& Collopy, 1992}),$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{n} \sum |A - F|, \quad (\text{Willmott \& Matsuura, 2005}),$$

$$\text{Mean Absolute Percentage Error (MAPE)} = \frac{1}{n} \sum \left| \frac{A - F}{A} \right| \times 100, \quad (\text{Armstrong \& Collopy, 1992}), \text{ and}$$

$$\text{Root Mean Square Error (RMSE)} = \frac{1}{n} \sum (A - F)^2, \quad (\text{Montgomery et al., 2012}),$$

where A represents the actual value, F represents the forecasted value, and n is the total number of predictors, are commonly used to assess the accuracy and relative efficiency of forecast models (Davydenko & Fildes, 2016). However, no single forecast accuracy measure is ideal, and the choice of the most appropriate error measure is often controversial (Koutsandreas et al., 2021).

Accuracy measures and comparisons of forecast models are often confused, but they are distinct concepts. Accuracy measures investigate the closeness of forecast values to observed values within a model while comparing models identifies the difference between the accuracy measures of different models (Hyndman & Athanasopoulos, 2014). MAE and MAPE are commonly used forecast errors in model comparisons (Hyndman & Athanasopoulos, 2014).

To assess the relative accuracy of different models, various simple benchmark methods, such as Average, Naïve, Seasonal Naïve, and Drift, are compared with the developed forecasting models (Hyndman & Athanasopoulos, 2016). The performance of a sophisticated method is evaluated against these simple alternatives, and if it is not superior, it may not be worth fitting (Hyndman & Athanasopoulos, 2016).

This paper clarifies the confusing notion between the accuracy measure of a forecast model and the comparison of forecast models, and, it illustrates a case of a multiple regression model fitted from time series data compared with the naïve forecast approach (detailed explanation in the materials and methods section) constructed from the same data. And the goal is, with the aid of the most accurate forecast errors for a certain situation or practice, it is hoped to establish a basis for comparing the relative accuracy of various forecast models.

2. Materials and Methods

Naive forecasting is a simple and basic model that assumes no trend, seasonality, or any other pattern in the data. As described by Monash University (n.d.), it is an estimating technique in which the last period's actuals are used as this period's forecast, without adjusting them or attempting to establish causal factors. This makes it a forecasting model that requires minimum effort and manipulation of data to prepare a forecast. Additionally, it is inexpensive to develop, store data, and operate. The naive approach is a commonly used benchmark for comparing forecast models in the field of forecasting.

According to OTexts (n.d.), naive forecasting is a simple approach in which all forecasts are set to be the value of the last observation. For a time series dataset $y_1, y_2, y_3, \dots, y_t$, where each observation represents a value at a specific time, the naive approach assumes that the next observation will be equal to the most recent observation. Therefore, the forecast for the next time period ($t + 1$) can be represented as, $y_{(t+1)} = y_t$.

Despite its simplicity, the naive approach can still be useful as a benchmark for more complex forecasting models. A few examples of a naive forecast model could be as follows: "The forecast for 1996 would be the observed value for 1995, the forecast for 1997 would be the observed value for 1996, and so on." Or, "If the store sold \$1000 worth of goods on Monday, the manager predicts sales of \$1000 for Tuesday."

The naive technique is often used as a standard for comparison (as a benchmark) for more complex forecast models, according to Makridakis et al. (1998) and Hyndman and Athanasopoulos (2016). Despite more sophisticated models performing better in terms of accuracy, the naive technique is still a useful tool for assessing and comparing different prediction models.

MAE and MAPE are widely used accuracy measures for comparing forecast methods (Hyndman & Athanasopoulos, 2018). They are easy to understand and compute. This study utilized these two measures to compare a forecast model developed by Dhakal (2018, p.95), which is represented as follows:

$$\text{Production} = -1619 + 5.26 (\text{harvested area}) - 0.239 (\text{rural population}) + 0.321 (\text{price at harvest}).$$

The model was found to be significant and useful for concerned planners and policymakers in forecasting rice production in the country. The study concluded that multiple regression models could be scientifically used for forecasting and could contribute to national-level rice production.

To assess the accuracy of the forecast models, a cross-validation approach was used, as recommended by Hyndman and Athanasopoulos (2014). This involved using at least 20% of the last parts of the total sample as test data to compute the forecast error while fitting a forecast model from time series data. The forecast accuracies for the multiple regression model and the naïve forecast model were computed and interpreted using the MAE and MAPE measures. The smaller these measures, the better the model when compared simultaneously.

3. Results and Discussion

The computed values of MAE and MAPE for the fitted multiple regression model and naïve forecast method for the test data are shown in the table below.

Error Metrics Computed for Model Comparison

Model	Forecast Error	
	MAE	MAPE
Multiple regression model	199.5848	4.77%
Naïve forecast method	240.44	5.80%

The multiple regression model yielded an MAE of 199.58, indicating an average forecast error of nearly 200 regardless of its sign. In comparison, the naïve forecast method had an MAE of 240.44. When comparing models generated from the same data set, the absolute size of the error is more meaningful in deciding the relative goodness of the models. Therefore, the fitted multiple regression model with a smaller MAE is deemed better than the naïve forecast method.

A relative comparison between the models based on MAPE showed that the multiple regression model had an error of 4.77, approximately 5% smaller than the naïve forecast method, which had an error of 5.80, approximately 6% of the forecasted value. Thus, from both the MAE and MAPE perspectives, the fitted multiple regression model is superior to the naïve forecasting approach.

4. Conclusion and Recommendation

This research article emphasizes the importance of distinguishing between the accuracy measures of forecast models and the comparison of forecast models. The study has demonstrated the comparison of a newly fitted multiple regression model with the widely used naïve forecasting approach using cross-validation methods. The results of the study suggest that the multiple regression model outperforms the naïve method in terms of both MAE and MAPE, indicating that the new fit is a worthwhile model. The study has also shown that the naïve approach remains a useful tool for evaluating and comparing different forecast models.

In future investigations, this research provides a basis for exploring other benchmark approaches for forecast model comparisons and developing improved techniques for comparing forecast models. It is recommended that future research explores the applicability of the multiple regression model to other contexts and datasets. Additionally, the development of more accurate and efficient forecast error measures for specific situations and practices should be explored.

References

- [1]. Armstrong, J. S., & Collopy, F. (1992). Error measures for generalizing about forecasting methods: Empirical comparisons. *International Journal of Forecasting*, 8(1),69-80.
- [2]. Chambers, J.C., Mulick, S.K., & Smith, D.D. (1971). How to choose the right Forecasting technique. *Harvard Business Review*. Accessed on 13 December 2016.
- [3]. Davydenko, A., & Fildes, R. (2016). Forecast Error Measures: Critical Review and Practical Recommendations. *Business Forecasting: Practical Problems and Solutions*. John Wiley & Sons Inc.
- [4]. Dhakal, C.P. (2018). Multiple regression model fitted for rice production forecasting in Nepal: A case of time series data. *Nepalese Journal of Statistics*, Vol. 2, 98-98, Central Department of Statistics, Tribhuvan University, Kirtipur, Kathmandu, Nepal.
- [5]. Forecasting. (2016). Investopedia. Accessed on 13 December 2016.
- [6]. Hyndman, R.J., & Athanasopoulos, G. (2014). *Forecasting: Principles and Practice*, an online textbook. Accessed on 17 January 2017.
- [7]. Hyndman, R.J., & Athanasopoulos, G. (2016). *Forecasting: Principles and Practice*, an online textbook. Accessed on 16 January 2017
- [8]. Hyndman, R.J., & Athanasopoulos, G. (2018). *Forecasting: Principles and Practice*, 2nd edition, Online Texts: Melbourne, Australia. Accessed on 26 February 2023
- [9]. Koutsandreas, D., Spiliotis, E., Petropoulos, F., & Assimakopoulos, V. (2021). On the selection of forecasting accuracy measures. *Journal of the Operational Research Society*.
- [10]. Makridakis, S., Wheelwrights, S.C., & Hyndman, R. J. (1998). *Forecasting methods and applications* (3rd ed.). John Wiley & Sons, Inc.
- [11]. Monash University. (2023). *Forecasting Techniques: Naive Approach*. Accessed on 26 February 2023.
- [12]. The different forecasting methods. (2016). *Theweatherprediction.com*. Accessed on 25 November 2016.
- [13]. Tuovila, A. (2022). *Forecasting: What It Is, how it's used in business and investing*. Investopedia. Accessed on 27 November 2022.
- [14]. Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research*, 30(1),79-82.

□ □