A Comparative Study of ARIMA And ETS Models in Forecasting U.S. Nonfarm Data

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Abstract. Time series forecasting is an essential reference for economic policies and their designs. Accurate predictions help to decrease uncertainty and guide the efficient allocation of resources. Nonfarm payroll in the United States is one of the most important economic indicators for evaluating the labor market and the overall expansion of the economy, while forecasting research that concentrates on this specific dataset remains scant. This paper constructs ARIMA and ETS models to forecast the U.S. nonfarm employment data and evaluates their performance. The optimal ARIMA and ETS specifications are selected based on the training dataset, and their forecasting accuracy is assessed using the RMSE metric. The results suggest that the ARIMA achieves higher accuracy of prediction compared to ETS. Through a systematic comparison of two forecasting approaches, this study provides evidence that ARIMA is more suitable for predicting U.S. nonfarm data, presenting useful information for economic forecasting research and the government and investors who favor labor market indicators.

Keywords: Time series forecasting; ARIMA model; ETS model; Nonfarm payroll.

1. Introduction

Forecasting responses is a fundamental issue in the decision-making processes of various domains. Reliable forecasts enable policymakers, businesses, and researchers to anticipate future developments, reducing uncertainty and supplying the basis for decisions. Therefore, continuous improvement of forecasting methods is essential for enhancing accuracy and adapting to emerging trends.

Upon reviewing the recent studies, numerous time series forecasting models have been developed to address the complex patterns and dynamic patterning. The most basic approach is to apply a single prediction model. For example, ARIMA models have demonstrated strong forecasting performance in forecasting stock prices and epidemic data [1-2]. Building on this, researchers added exogenous variables with ARIMAX models, proving effective in capturing the dynamics of agricultural output [3]. Extensions such as SARIMA further improved predictive ability, successfully modeling the seasonal patterns of precipitation, temperature, and commodity prices [4-5]. Beyond classical parametric models, deep learning has become a major focus in time series research. CNNs capture local temporal features through convolution operations and have great accuracy in large-scale forecasting tasks [6]. RNNs and their variants are widely used in traffic flow and meteorological forecasting due to their ability to learn temporal dependencies [7]. Transformer models exhibit clear advantages in capturing long-term dependencies [8]. In addition to single models, hybrid approaches have been explored to improve accuracy. For example, combining ARIMA with LSTM, the accuracy of oil production forecasting has been significantly improved, and the integration of LSTM with Neural Prophet has achieved high effectiveness in the context of electric load forecasting [9-10]. Overall, research on time series forecasting has advanced rapidly. However, studies focusing on U.S. nonfarm data remain limited. Since this dataset directly reflects macroeconomic activity, its forecasts have important implications for policymaking and market expectations, yet current literature provides little systematic exploration of this domain.

This study seeks to evaluate the suitability of two structural models, ARIMA and ETS, in predicting U.S. nonfarm employment. The dataset is sampled between 1939 and 2008 for model fitting, whereas a period from 2008 to 2025 is used for testing the accuracy. By fitting the training data and assessing the RMSE, the outcomes indicate that the ARIMA model is more suitable for predicting the nonfarm payroll employment. ARIMA and ETS are both very commonly employed time series methods for forecasting, and this comparative approach demonstrates the superiority of ARIMA as well as its advantage in filling the void in the research on forecasting the U.S. nonfarm employment data.

2. Data

The U.S. nonfarm payroll employment (PAYEMS) series measures the total number of paid employees in the economy, excluding those working on farms, in private households, and for nonprofit organizations. It provides valuable insights into the current economic conditions, as it reflects the number of jobs added or lost within an economy. Given its significant implications, it is closely monitored by policymakers, investors, and researchers, making the forecasting of this dataset particularly important.

The dataset used in this study is the seasonally adjusted U.S. nonfarm payroll employment (PAYEMS) from the Bureau of Labor Statistics (BLS), accessed via FRED (https://fred.stlouisfed.org/series/PAYEMS). It covers the period from January 1939 to August 2025. The data have been seasonally adjusted to remove recurring seasonal effects, and the overall trend of the series is illustrated in Fig. 1.

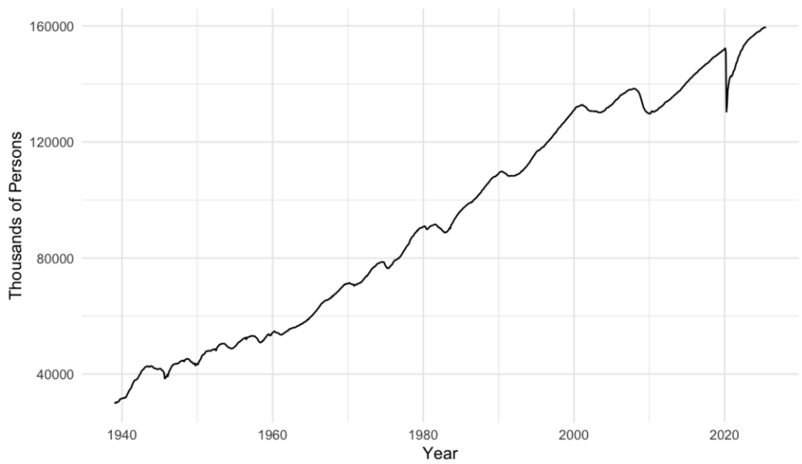

Fig. 1 U.S. nonfarm payroll employment

Fig. 1 presents the series from 1939 to 2025. The data show a clear long-term upward trend with downturns during recessions, most notably the sharp decline in 2020 due to the COVID-19 pandemic, followed by a rapid recovery. It reflects sustained economic and labor force growth. The summary statistics of the PAYEMS time series are provided in Table 1.

Table 1. Descriptive Statistics

	mean	SD	max	min	kurtosis	skewness
PAYEMS	93090.64	38503.64	159539	29923	1.58	0.05

Table 1 reports that the mean value is about 93,091 thousand people, with a standard deviation of 38,504, indicating substantial long-term growth but also large fluctuations over the period. The maximum is 159,539 occurred in July 2025, whereas the minimum equals 29923, corresponding to early years of the dataset. The kurtosis is 1.58, suggesting that the distribution is more peaked than the normal distribution. The skewness is 0.05, close to zero, indicating that the distribution is approximately symmetric around its mean.

3. Method

3.1. ARIMA

As one of the most classic time series models, the ARIMA model finds extensive application across multiple domains, including but not limited to financial forecasting, economic analysis, and public health surveillance. The model integrates three core components to capture the features in the time series: the Autoregressive (AR), Integrated (I), and Autoregressive AR(p). The Autoregressive AR(p) term can explain the correlation within the series. It constructs a forecasting framework by analyzing the temporal dependencies within the series, which can be expressed as:

$$y_t = c + \varphi_1 y_{\{t-1\}} + \varphi_2 y_{\{t-2\}} + \cdots + \varphi_p y_{\{t-p\}} + u_t \tag{1}$$

The time series yt is referred to as a p-th order autoregressive process. The coefficients φ, known as *autoregressive coefficients,* are key parameters in the model that describe the linear relationship between the current value and its past lagged values. They must be estimated from the data. The ut is an independent white noise series representing the random term and is uncorrelated with the lagged variables. The integrated (I) term ensures stationarity through differencing. By applying d-order differencing, the differencing stabilizes the mean of a time series and removes variation patterns, thereby eliminating trends and seasonality. Generally, the number of differences does not exceed two. The MA(q) moving average model can process the cumulative effect provided by random error terms in time series forecasting. It can be written as

$$y_t = \mu + u_t + \theta_1 u_{\{t-1\}} + \theta_2 u_{\{t-2\}} + \cdots + \theta_q u_{\{t-q\}} \tag{2}$$

μ is a constant. The parameters θ serve as the moving average coefficients to be estimated. The term ut, as in the AR(p) process, represents a sequence of independent white noise terms. In modeling, the above three components are combined: the data is first differenced d times, and then the differenced series is fitted using the following ARMA(p,q) model:

$$y_t = c + \varphi_1 y_{\{t-1\}} + \varphi_2 y_{\{t-2\}} + \cdots + \varphi_p y_{\{t-p\}} + u_t + \theta_1 u_{\{t-1\}} + \theta_2 u_{\{t-2\}} + \cdots + \theta_q u_{\{t-q\}} \tag{3}$$

Thus, an ARIMA(p,d,q) model is constructed.

3.2. ETS

The Exponential Smoothing State Space (ETS) framework offers a unified extension of single, double, and triple exponential smoothing methods. It systematically captures error, trend, and seasonal components, allowing for a more flexible and robust analysis of time series. Each one of these components can be specified as additive, multiplicative, or none, forming a highly diverse family of models. Trend, which is the indicator of the general upward or downward movement in a time series, reflects overall directional changes. Seasonality captures the recurring fluctuation patterns in the series caused by seasonal, cyclical, or other regular events. The error term captures the unpredictable deviations between observed and fitted values, reflecting the unpredictable, random disturbances inherent in the time series. In addition, ETS allows for the incorporation of a damped trend, in which the trend effect gradually diminishes over the forecast horizon, enhancing the stability of long-term forecasts.

4. Result

In this study, the period from January 1939 to March 2008 is used as the training set, and the period from April 2008 to July 2025 is designated as the test set. By fitting the training data, the following ARIMA and ETS model parameters are obtained (See Table 2).

Table 2. Parameter Results

	Parameter 1	Parameter 2	Parameter 3
ARIMA	2	1	2
ETS	A	Ad	N

From Table 2, the optimal ARIMA model is ARIMA (2,1,2). p=2 indicates that the model captures the dependence on the two most recent observations; d=1 denotes that the series is differenced once to remove trend and achieve stationarity; and q=2 means that the model includes two moving average terms to account for the correlation between the current error and the errors from the previous two periods. The optimal ETS model is ETS (A, Ad, N), which represents an exponential smoothing method with additive errors, an additive damped trend, and no seasonality. Based on the above-mentioned parameters, the forecasting results are shown in Fig. 2. From Fig. 2, ARIMA model follows the actual trend more closely and provides a narrower prediction interval. This study assesses the forecasting accuracy of the two models by applying RMSE to measure the deviation between forecasts and observed data (See Table 3).

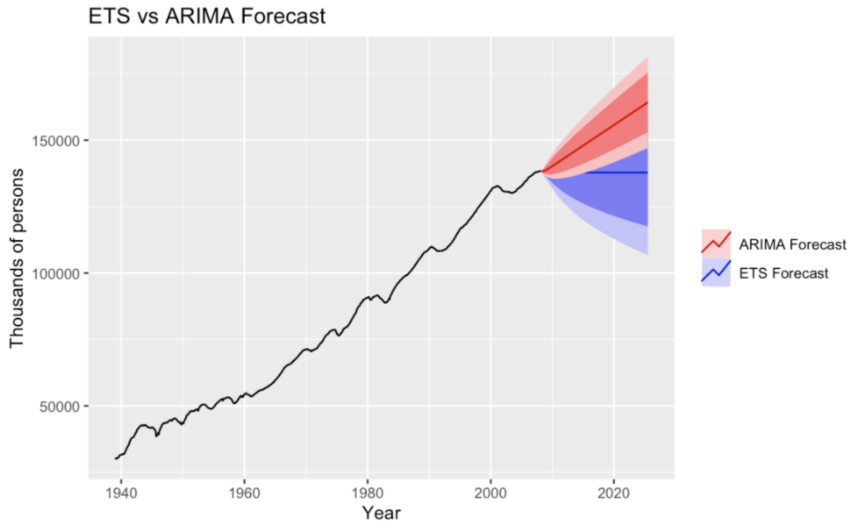

Fig. 2 ARIMA vs ETS Result

Table 3. RMSE Results

Model	RMES
ARIMA	8297.2404
ETS	10611.454

From Table 3, it can be observed that the RMSE of the ARIMA model is 2,314 lower than that of the ETS model. A smaller RMSE indicates higher predictive accuracy. Therefore, the ARIMA model outperforms the ETS model in overall forecasting performance and more effectively captures the actual data trend.

5. Conclusion

This paper has examined the applicability of two classical time series models, ARIMA and ETS, in forecasting U.S. nonfarm data. Using data from 1939 to 2008 for model estimation and 2008 to 2025 for validation, the study selected optimal model specifications and assessed predictive accuracy through the RMSE criterion. The findings clearly indicate that ARIMA offers better forecasting accuracy than ETS, suggesting that ARIMA can more effectively capture the dynamic characteristics of the series. This research demonstrates the relative advantage of ARIMA in predicting U.S. nonfarm data and provides fresh empirical evidence to inform economic forecasting practices. The results contribute not only to the academic literature on time series modeling but also to the needs of policymakers and market participants.

In future research, the scope can be extended beyond ARIMA and ETS models by incorporating machine learning techniques. Moreover, since the results are based solely on U.S. nonfarm data, their generalizability to other macroeconomic indicators or different national contexts may be limited.

References

[1] Khan S, Alghulaiakh H. ARIMA model for accurate time series stocks forecasting. International Journal of Advanced Computer Science and Applications, 2020, 11(7).

[2] Benvenuto D, Giovanetti M, Vassallo L, et al. Application of the ARIMA model on the COVID-2019 epidemic dataset. Data in Brief, 2020, 29: 105340.

[3] Pandit P, Sagar A, Ghose B, et al. Hybrid time series models with exogenous variable for improved yield forecasting of major Rabi crops in India. Scientific Reports, 2023, 13(1).

[4] Pokhrel A, Adhikari R. Leveraging exogenous insights: a comparative forecast of paddy production in Nepal using ARIMA and ARIMAX models. Economic Review of Nepal, 2023, 6(1): 52-69.

[5] Divisekara R W, Jayasinghe G J M S R, Kumari K W S N. Forecasting the red lentils commodity market price using SARIMA models. SN Business & Economics, 2020, 1(1).

[6] Lim B, Zohren S. Time-series forecasting with deep learning: a survey. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 2021, 379(2194): 20200209.

[7] Fang W, Chen Y, Xue Q. Survey on research of RNN-based spatio-temporal sequence prediction algorithms. Journal on Big Data, 2021, 3(3): 97-110.

[8] Liu X, Wang W. Deep time series forecasting models: a comprehensive survey. Mathematics, 2024, 12(10): 1504.

[9] Fan D, Sun H, Yao J, et al. Well production forecasting based on ARIMA-LSTM model considering manual operations. Energy, 2020, 220: 119708.

[10] Shohan M J A, Faruque M O, Foo S Y. Forecasting of electric load using a hybrid LSTM-neural prophet model. Energies, 2022, 15(6): 2158.