

Comparative Analysis of Forecasting through Exponential smoothing and Auto Regressive Integrated Moving Average

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Abstract:

Forecasting is a critical component of decision-making in various fields, including finance, economics, supply chain management, and climate studies. Accurate forecasting methods enable organizations to plan and allocate resources efficiently. Among the numerous time series forecasting techniques, Holt's Exponential Smoothing (HES) and Auto-Regressive Integrated Moving Average (ARIMA) are widely utilized due to their robustness and versatility. HES is well-suited for capturing trends and seasonality in time series data through a weighted smoothing approach, whereas ARIMA models rely on statistical properties to account for autoregressive and moving average components. While both methods are effective, their performance often varies depending on the nature of the data, making comparative analysis a critical research area. This study aims to compare the accuracy, applicability, and limitations of HES and ARIMA models through empirical analysis on real-world datasets, providing insights into their suitability for different forecasting scenarios.

Key Words:

Exponential, Regressive, Smoothing, Machine learning, Economic

Introduction:

Time series forecasting is an essential tool for analyzing historical data and predicting future trends in areas such as finance, supply chain management, and environmental studies. Among the numerous forecasting techniques available, Holt's Exponential Smoothing (HES) and Auto-Regressive Integrated Moving Average (ARIMA) are two of the most widely used models due to their effectiveness and adaptability to different types of data. Holt's

Exponential Smoothing is an extension of simple exponential smoothing that accounts for trends in the data, making it particularly suitable for datasets with consistent upward or downward movements. On the other hand, ARIMA is a statistical approach that combines autoregression, differencing, and moving averages to model time series data. While both methods are designed to produce accurate forecasts, their performance often depends on the characteristics of the dataset, such as trend, seasonality, and noise. This study seeks to explore and compare the strengths, limitations, and accuracy of HES and ARIMA models in forecasting, providing a deeper understanding of their practical applications.

The application of time series forecasting methods, particularly Holt's Exponential Smoothing (HES) and ARIMA, has been extensively explored in the literature. Holt (1957) introduced the exponential smoothing technique to capture trends in time series data by assigning exponentially decreasing weights to past observations, laying the foundation for

modern trend-based forecasting methods. Later developments expanded the model to include seasonality, further enhancing its ability to handle complex datasets (Gardner, 1985). HES has since been widely adopted due to its simplicity, computational efficiency, and ability to handle non-seasonal and trend-based data effectively.

Forecasting economic indicators such as per capita income is critical for policymakers, businesses, and researchers to make informed decisions regarding resource allocation, investment planning, and policy development. Accurate forecasting models enable a better understanding of future economic trends and contribute to strategic planning at both macroeconomic and microeconomic levels. Among the numerous time series forecasting techniques, Holt's Exponential Smoothing (HES) and Auto-Regressive Integrated Moving Average (ARIMA) are widely recognized for their robustness and reliability. HES is a smoothing-based method that is particularly effective for capturing trends in non-stationary data, while ARIMA is a statistical model that excels in identifying and predicting patterns by leveraging autoregressive and moving average components.

This study focuses on comparing the forecasting accuracy and performance of these two widely used methods to predict the per capita income of the next five years. By analyzing historical per capita income data, the study aims to assess the suitability of each model under varying data conditions, providing valuable insights into their applicability for long-term economic forecasting. The results will contribute to a deeper understanding of how these methods can be employed to forecast economic indicators and support evidence-based decision-making.

Forecasting economic indicators such as per capita income has been a significant area of research, as accurate predictions can assist in policy formulation, investment decisions, and long-term planning. Among the various forecasting techniques available, Holt's Exponential Smoothing (HES) and Auto-Regressive Integrated Moving Average (ARIMA) are two widely used time series models that have been extensively explored in the literature.

Holt's Exponential Smoothing, developed by Holt (1957), is an extension of simple exponential smoothing designed to handle data with trends. The model applies exponentially decreasing weights to past observations, allowing it to capture both level and trend components in non-seasonal data effectively. Gardner (1985) emphasized the flexibility and simplicity of exponential smoothing methods, making them suitable for short- to medium-

term forecasting. HES has been successfully applied in various domains, such as demand forecasting, energy consumption, and economic indicators, where data exhibit clear trends.

ARIMA models, first formalized by Box and Jenkins (1976), offer a more statistically rigorous approach to time series forecasting. By combining autoregressive (AR) terms, differencing (I) for non-stationarity, and moving average (MA) terms, ARIMA models can effectively handle diverse patterns in time series data. Hyndman and Athanasopoulos (2018) highlighted ARIMA's ability to adapt to complex, linear relationships in data and its flexibility in modeling both stationary and non-stationary series. ARIMA has been widely used in forecasting macroeconomic variables such as GDP, inflation, and income due to its robust theoretical foundation and proven accuracy.

Comparative studies of HES and ARIMA have revealed contrasting strengths of these models depending on the dataset characteristics. Makridakis et al. (1982), in the famous M-Competition, found that while ARIMA models tend to outperform smoothing techniques on data with strong autocorrelation, exponential smoothing methods are often more reliable for simpler, trend-dominated datasets. Ord et al. (1997) supported this view, noting that HES is computationally efficient and effective for stable patterns, whereas ARIMA excels in cases with more complex dynamics.

Several researchers have also applied these methods specifically to economic forecasting. For instance, Adhikari and Agrawal (2013) demonstrated the effectiveness of ARIMA in forecasting per capita income in India, highlighting its ability to capture the inherent trends and fluctuations in economic data. Similarly, exponential smoothing methods have been shown to perform well for economic indicators with consistent growth trends (Padhan, 2012). Despite their individual strengths, both HES and ARIMA have limitations. HES may struggle with capturing intricate seasonal or autocorrelated patterns, while ARIMA often requires more complex model specification and assumptions, such as stationarity. Recent studies have also explored hybrid approaches that combine these techniques to improve forecasting accuracy.

This review establishes the foundation for comparing the performance of HES and ARIMA models in forecasting per capita income. Given the importance of accurate income projections in economic planning, this study seeks to contribute to the existing literature by identifying the most suitable forecasting approach for projecting future trends in per capita income.

Objectives of the study

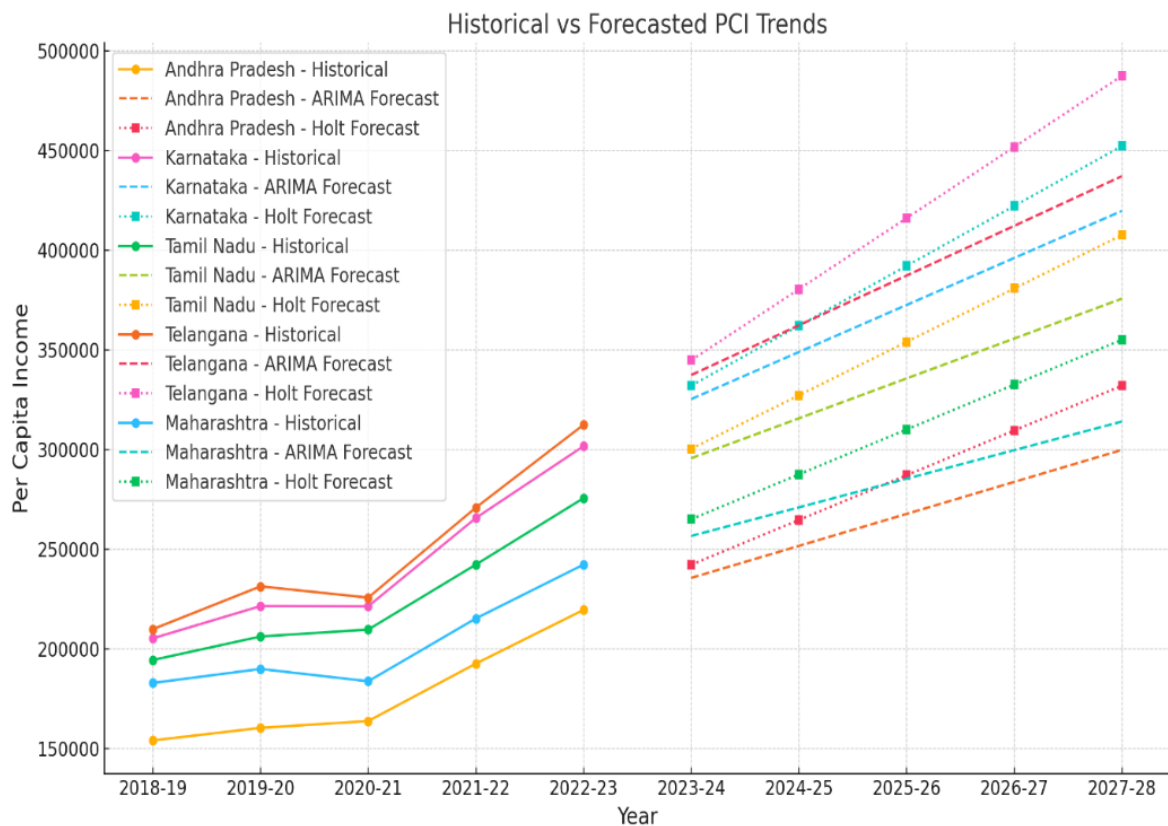
- To forecast per-capita income of Indian States using Holt's Exponential smoothing and ARIMA model.
- To evaluate the performance of the ARIMA and Holt's Linear Trend models for forecasting per capita income.
- To implement policies regarding economic development.

Literature Review:

AUTHOR	METHODS USED	FINDINGS
Taylor (2003)	ES Method	ES methods could be adapted to address specific forecasting challenges
Khashei & Bijari (2011)	ARIMA &ANN Method	The hybrid model outperforms traditional models in terms of accuracy.
M. Prochniak & B. Witkowski (2013)	β -convergence analysis and Bayesian averaging of classical estimates.	convergence among the transition economies and the catch-up process is conditional, meaning that the individual countries converge toward their own steady states. The convergence parameter (β) implies a very slow pace in the catch up the process.
A.A. Sofi, R.S. Durai S. (2017)	Parametric and non-parametric methods used to test absolute and conditional convergence.	Empirical data reveals that Indian states are diverging in absolute sense and converging on conditional basis.
Chakraborty & Joseph (2017)	econometric and machine learning models	They find that while machine learning models offer better accuracy in certain cases, traditional econometric models still hold value, especially when interpretability and understanding of economic relationships are crucial.
B. Micallef (2020)	linear regression using OLS, Sigma Convergence	beta and sigma convergence is only found
Chen & Wang (2022)	Convolutional Neural Networks (CNNs) in conjunction with LSTM	Both spatial and temporal patterns in the data, offering more accurate forecasts.
Ghosh & Das (2022)	Integrates Random Forests, Support Vector Machines (SVMs), and	The ensemble approach provided robust and accurate predictions by

	traditional time series models.	leveraging the strengths of each model
Kumar & Shankar (2023)	combining ARIMA with Gradient Boosting Machines	The study found that the hybrid model reduced forecasting errors compared to using either method alone
Liu et al. (2023)	Application of deep learning techniques, particularly Long Short-Term Memory (LSTM) networks	Found that model outperform the traditional econometric models by capturing complex, non-linear relationships in income data.

Methodology: ARIMA and Holt’s forecasting model is used to forecast the per capita income for the next five years for each state. Through python programming, error metrics for both methods using mean absolute error, root mean square error and mean absolute percentage error are calculated. Compound annual growth rates are calculated for variation study. These metrics are used for comparative analysis to identify potential economic growth patterns and regional disparities.



The chart above compares the actual per capita income of states with forecasts for using ARIMA and Holt's Linear Trend models.

The table below shows the compound annual growth rate.

Compound Annual Growth Rate

State	Historical 2018-23	ARIMA 2023-28	Holt's 2023-28
Odisha	11.208965	7.248492	10.027931
Madhya Pradesh	11.080867	7.291992	9.358112
Telangana	10.458935	6.949237	9.304883
Karnataka	10.107262	6.825547	8.433192
Rajasthan	10.012346	0.181728	9.017717
Assam	9.968027	0.250714	9.126652
Andhra Pradesh	9.261083	6.430385	8.624763
Tamil Nadu	9.119941	6.391659	8.141194
Meghalaya	8.069207	5.872729	3.158911
West Bengal	7.998279	5.724597	8.296479
Haryana	7.395719	5.427286	7.689176
Maharashtra	7.283258	5.326211	7.946371
Chhattisgarh	7.033059	5.224221	7.136084
Uttarakhand	5.830278	4.468064	6.833937
Punjab	4.916622	3.926296	4.265556
Odisha	11.208965	7.248492	10.027931
Madhya Pradesh	11.080867	7.291992	9.358112

Comparative Analysis of ARIMA and Holt's Linear Trend Forecast Models

Aspect	ARIMA	Holt's Linear Trend
Performance Metrics	- MAE: 12,566.93 - MSE: 203,971,707 - MAPE: 5.99% - RMSPE: 6.37%	- MAE: 18,536.89 - MSE: 408,602,173 - MAPE: 9.21% - RMSPE: 9.56%
Accuracy	Lower MAE, MSE, MAPE, and RMSPE. Forecasts closely align with actuals for most states.	Higher errors indicate less accurate forecasts. Deviations are noticeable, especially in states with non-linear growth.
Trend Capturing	Effectively captures underlying trends and seasonality in economic data.	Assumes linear growth, which may oversimplify real-world economic trends.
Adaptability	Requires parameter tuning (AR, MA, differencing), which allows flexibility in modeling different patterns.	Limited adaptability due to its linear assumption; may miss complex patterns.
Forecast Interpretation	Provides more reliable mid-term predictions; suitable for dynamic economic changes.	Better for long-term trends if linearity is a reasonable assumption.
Strengths	- Superior in capturing short- to mid-term trends. - Handles variability in growth rates effectively. - Suitable for states with high economic volatility.	- Simple implementation. - Useful for states with steady and predictable growth.
Weaknesses	- Sensitive to parameter choice. - Requires periodic re-evaluation and tuning. - May struggle with abrupt, external disruptions.	- Assumes linear trends, leading to inaccuracies in non-linear scenarios. - Limited in reflecting economic shocks or rapid changes.

Key Takeaways from the Analysis

- ARIMA forecast closely aligns with actual values for most states, showing its strength in capturing trends effectively.
- Holt's forecast exhibits larger deviations, especially for states with nonlinear growth patterns (e.g., Telangana, Karnataka).

- The gap between forecasts emphasizes the need for model selection based on economic context and growth dynamics.
- Odisha, Madhya Pradesh, and Telangana exhibit the highest growth rates, with Odisha leading at 11.2%.
- Punjab shows the lowest growth rate at 4.92%.
- Odisha and Madhya Pradesh maintain strong growth projections at ~7.2%.
- Rajasthan and Assam show minimal growth in ARIMA projections.
- Holt's projections generally show higher growth rates compared to ARIMA, with Odisha again leading at 10.03%.
- Meghalaya has significantly lower growth (3.16%), suggesting discrepancies in its trajectory.
- The ARIMA model provides significantly better accuracy, making it a more reliable forecasting tool.
- Holt's model overestimates in many cases, particularly for states with faster economic growth like Karnataka and Telangana.
- States with more volatile or non-linear growth patterns (e.g., Telangana, Andhra Pradesh) are better modelled by ARIMA.
- For states with stable growth trajectories (e.g., Punjab, West Bengal), Holt's performance is closer to ARIMA but still less accurate.
- ARIMA is the best for guiding short- to mid-term economic policies, given its ability to adapt to dynamic changes.
- Holt's may serve as a baseline for long-term planning, particularly in less dynamic states or regions.

Conclusion

ARIMA is the stronger forecasting tool due to its better overall performance in capturing economic trends and its adaptability to diverse state-level growth patterns. While ARIMA is recommended for most scenarios, Holt's may supplement it in cases where long-term linear projections are acceptable. Telangana, Karnataka, Tamil Nadu, and Haryana lead the economic growth in both current and projected per capita income. Assam, Rajasthan, and Meghalaya are projected to grow slowly, potentially widening the income gap with other states. This analysis indicates a need for targeted regional policies to boost economic growth in lagging states to ensure a more balanced economic landscape across the country. These trends provide valuable insights for policymakers aiming to address income disparities and promote inclusive growth across Indian states. Based on the analysis, the policy recommendations like Support for lagging states, encouraging regional specialization, strengthening education and healthcare, Boosting MSME sectors, Improve Governance and Policy Execution, Investing Renewable Energy, Focusing on Balanced Urbanization, poverty alleviation program, Monitoring and Addressing Regional Disparities etc. By implementing these policy measures, the government can address the widening income disparities, improve economic prospects for lagging states, and foster inclusive and sustainable growth across India.

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