# School of Management

## Coursework Submission Sheet

| **Student name(s)** | **%** | | **%** |
|---|---|---|---|
| **Rishika Jain** | | | |
| | | | |
| | | | |

For group work – individual % contributions need to be stated **only** where they **are not equal.**

**Department (e.g. Management):** **Management**

**Programme and Year of Study:** **MSc Business Analytics 2024-25**

**Name of lecturer:** **Dr. Fotios Petropoulos**

**Unit title and code** (eg MN20010)**:** MN50751

**Number of pages in assignment: 16** **Word count: 3829**

**Declaration**

I/we certify that I/we have read and understood the entry in the relevant Student Handbook for the School of Management on Cheating and Plagiarism and that all material in this assignment is my/our own work, except where I/we have indicated with appropriate references. I/we agree that, in line with Regulation 15.3(e), if requested I/we will submit an electronic copy of this work for submission to a Plagiarism Detection Service for quality assurance purposes. I/we also confirm that the percentage allocation of work is as shown above.

**Upload** your coursework via the Unit's Moodle Page by the specified submission date and time. For **Moodle submissions,** this form should be available on Moodle site for the relevant unit and can be pasted into the front page of your assignment if requested by your tutor. Copies are also available from Management Reception.

You should aim to hand your work in before the deadline given by your lecturer/ tutor. The University guidelines on penalties for late submission are as follows:

Any assessment submitted late without an agreed extension, will receive a maximum mark of 40% or the relevant pass mark. Any assessment submitted more than 5 working days without an agreed extension will receive a mark of zero.

For all **Moodle Submissions**, your marks and feedback should be returned to you via Moodle.

All work is internally moderated. For all work that contributes towards a final degree classification, a sample of work with supporting documentation for each unit is sent to an External Examiner for review and comment.

Please note that any mark given is provisional and is subject to confirmation by the relevant Boards of Examiners for Units, Programmes and Boards of Studies. These normally take place at the end of each Semester.

**COURSEWORK – BUSINESS STATISTICS AND FORECASTING**

## EXECUTIVE SUMMARY

This report focuses into predicting methods leveraging time series data from the M3 competition, library of the R software which contains ID’s within [701,1400]. The goal is to manually fit three models that is regression, exponential smoothing, and ARIMA. These models are fitted to a specific time series and assess their forecasting accuracy. Batch forecasting is then applied to various time series utilizing automatic approaches such as exponential smoothing, ARIMA, and a user-defined model selection strategy. The findings are assessed using different forecasting accuracy criteria and compared to benchmark models like Naive and Damped Exponential Smoothing. The analysis critically evaluates each forecasting method's applicability and considers the ramifications for real-world business forecasting applications.

## INTRODUCTION

In today's rapidly changing market conditions, effective forecasting is an essential tool for managers in a wide range of businesses, including banking, retail, healthcare, and manufacturing. Companies that can properly estimate future demand can optimize their resources, improve inventory management, and increase customer happiness.

The reliability of forecasts is heavily determined by the quality of the underlying data and the forecasting models used. Time series forecasting, which uses historical data to estimate future values, is especially beneficial for processes that are predicted to repeat over time. To manage varied data patterns such as trends, seasonality, and noise, a variety of forecasting approaches are available, including regression analysis, exponential smoothing, and ARIMA models.

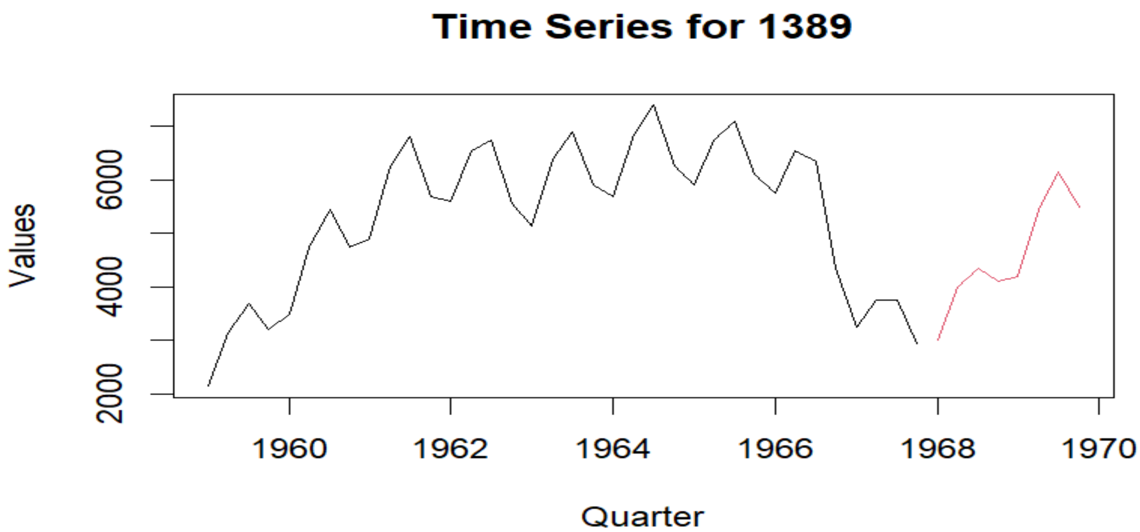
It looks at two major aspects of time series forecasting: manual modeling and batch forecasting. The first step entails selecting and applying three different forecasting models (regression, exponential smoothing, and ARIMA) to a given time series dataset. We want to see how well these models capture the underlying patterns in the data. The second section digs into batch forecasting, which involves applying automatic exponential smoothing and ARIMA models to a larger amount of time series data and comparing their performance using multiple error metrics.

The report looks at the performance of these strategies and makes advice to businesses on how to select the best forecasting approach based on the unique qualities of their data. It will also investigate the merits and shortcomings of each model, providing insights into their real-world usability.

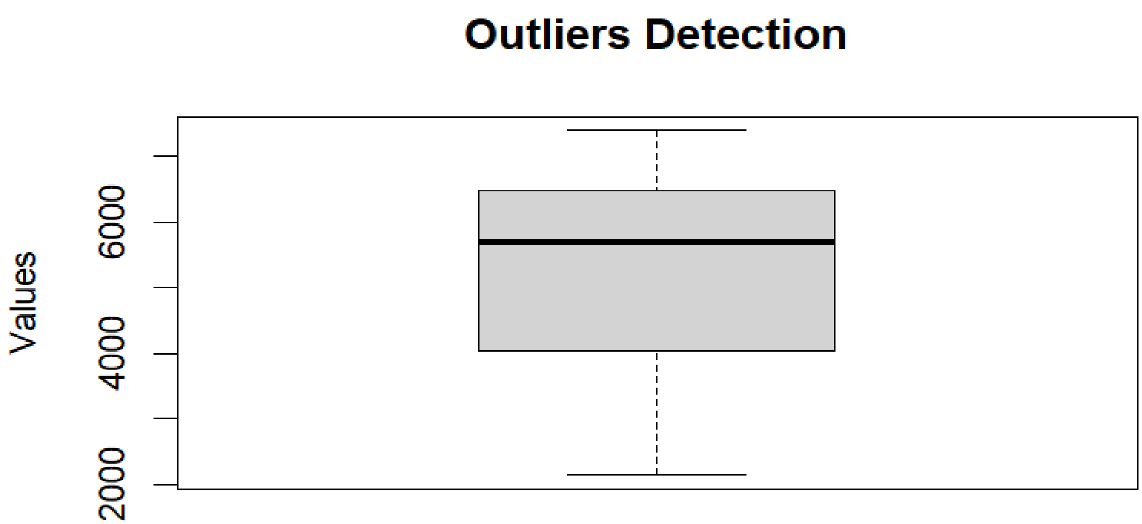
**MANUAL MODELLING**

## DATA EXPLORATION

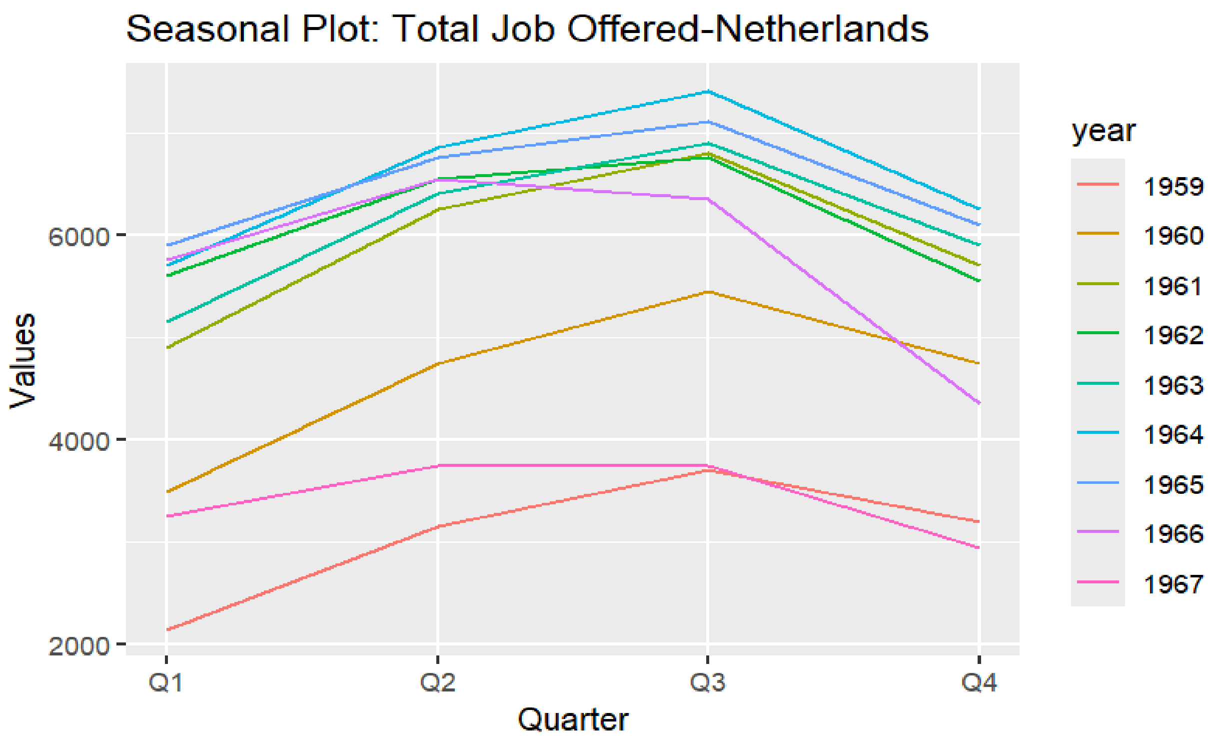
The first step of the analysis included an extensive review of historical data on total jobs vacant and jobs offered in the Netherlands. This phase involved visually inspecting the data to determine the trend, which demonstrated a steady upward slope, indicating a steadily rising job market. Further analysis uncovered reoccurring patterns, such as seasonal oscillations.

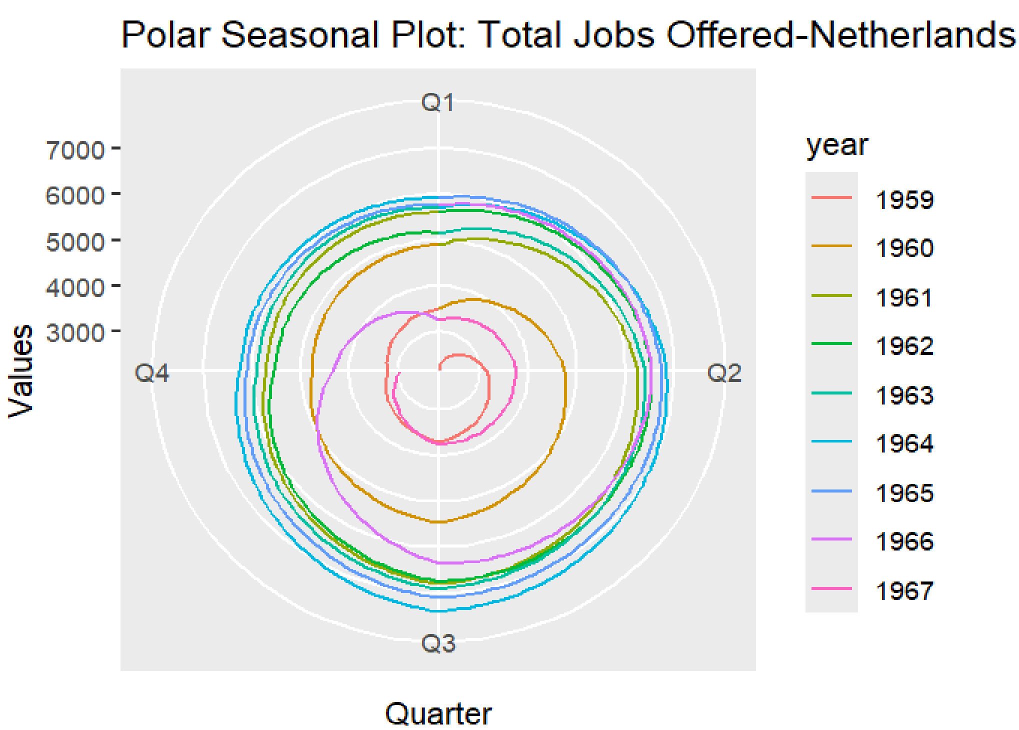



A rigorous statistical analysis was carried out to acquire a better grasp of the data's features. The average number of job offers was at 5,329, with a standard deviation of 1,407, showing a moderate amount of variability. The data showed a little negative skew, indicating that a higher number of observations were above average. It also discovered unexpected values known as outliers, which could distort the results. These outliers were then represented with a boxplot.




To further study seasonal patterns, specialized plots were used to analyze how job offers changed throughout the year, revealing consistent patterns across different quarters. Finally, multiple techniques were used to deconstruct the time series, effectively distinguishing the overall trend from the natural seasonal fluctuations and detecting any remaining unexplained variances. This extensive exploratory phase laid a firm basis and gave crucial insights into the major attributes and underlying causes of the job offer data, which were required for the future creation of an accurate forecasting model.



## REGRESSION MODELLING, ANALYSIS AND FORECASTING

Several regression models were used to forecast the number of vacant and available jobs in the Netherlands. These models included trend, seasonality, and their interactions, as well as transformations such as square root and logarithmic to increase model fit. Models with quadratic trend components were also examined to capture any nonlinear patterns in the data. Each model was extensively evaluated based on its fit to historical data and extensive residual diagnostics.

### Model Selection and Evaluation

The performance metric known as modified R-squared was used to determine the best-fitting model. This statistic determines how well the model describes the data while taking into consideration the amount of variables incorporated. A higher adjusted R-squared value suggests a stronger model. After considering numerous models, the most appropriate model was found to include a trend, seasonal changes, and a quadratic factor. This model efficiently caught both overall upward movement and seasonal oscillations, making it the best option for correctly representing observed data patterns.

| Model | Adjusted R square | F-statistic | P-value |
|---|---|---|---|
| Trend | 0.01607 | 1.572 | 0.2185 |
| Trend and Seasonality | 0.08846 | 1.849 | 0.1446 |
| Trend and Seasonality Interaction | 0.2376 | 1.122 | 0.3776 |
| Log Transformation | 0.6245 | 1.583 | 0.2036 |
| **Polynomial Transformation** | **0.8929** | **59.34** | **1.97** |

The most suitable model included a trend, seasonality, and a quadratic trend term. This model provided an accurate fit to the data, capturing both the overall increasing trend and seasonal variability.

After selecting the model, the residuals were thoroughly evaluated. The residuals, which represent the disparities between actual observations and model predictions, were analysed to determine model adequacy and find any systemic biases or unexplained changes.

Tashman (2000) emphasizes the importance of residual analysis in validating a model's predictive reliability, stating that residual patterns should be random with no identifiable tendencies. Similarly, Hyndman and Koehler (2006) suggest using residuals to assess the quality of forecasting models, emphasizing the importance of residual normality and the absence of autocorrelation.

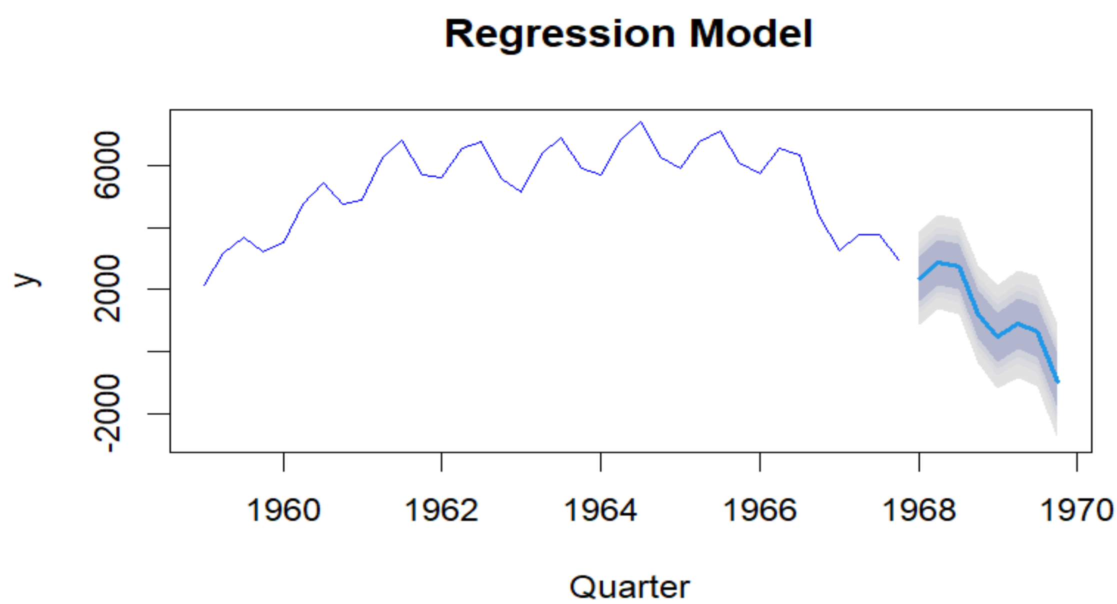
The residual diagnostics provided several valuable insights:

1. **Residual Pattern**: Recurring patterns in residuals indicate that the model may not have fully captured the data's nuances over time. This shows that there is still room to improve the model's accuracy.
2. **Autocorrelation**: The residuals showed significant correlations across time, indicating that the model may not have adequately accounted for time-related changes. Further refining is needed to improve performance.
3. **Normality of Residuals**: Residuals were generally symmetric, but not perfectly so. This suggests that the model can yet be improved to better fit the data.

Despite attempts to fit the data using various transformations, the residual diagnostics remained constant. This shows that, while the model did a reasonable job of capturing overall patterns and seasonality, there is still room for improvement. Refining the model to better address time-related dependencies and enhance residual distributions may result in more accurate forecasts in the future.

**Forecasting Results**

The selected model was used to generate forecasts for the next eight quarters. The forecasts are presented in a visual format. The blue line represents the point forecast and the shaded area illustrating the prediction interval, which widens as the forecast horizon extends, reflecting increasing uncertainty.



## EXPONENTIAL SMOOTHING MODELLING, ANALYSIS AND FORECASTING

Exponential smoothing is a systematic strategy to model trends and seasonal changes that emphasizes recent observations. The aim is essentially to find the best-fitting exponential smoothing model to generate accurate forecasts while balancing predictive performance and interpretability. This section demonstrates the utility of Exponential Smoothing State Space (ETS) models and their adaptation to varied datasets, as illustrated with data from the Mcomp package.

In this, a variety of ETS models, including ETS(ANN), ETS(AAN), ETS(AAdN), and ETS(AAA), were used to assess their capacity to account for error, trend, and seasonality. Additive and damped trends, as well as models with and without seasonal adjustments, were evaluated to ensure that the chosen model matches the dataset's key properties. This is in line with Gardner's (2006) evaluation of exponential smoothing approaches, which emphasizes their adaptability across many forecasting contexts.

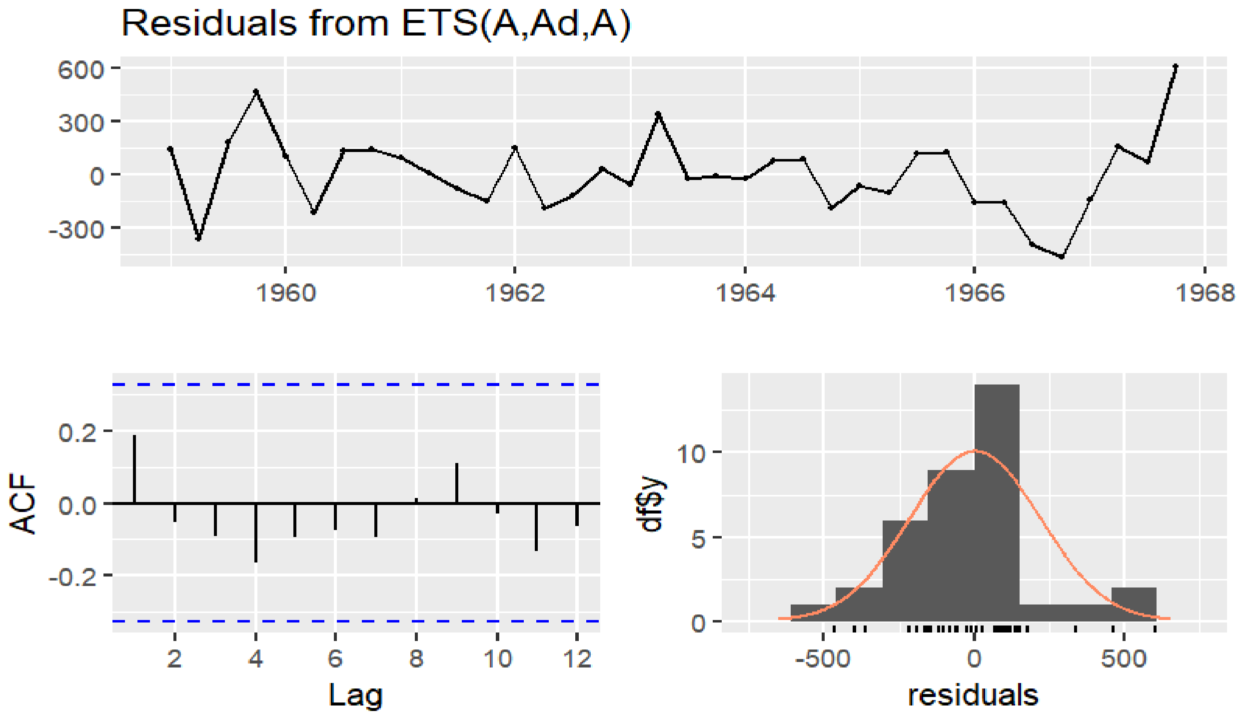
### Model Selection and Evaluation

To identify the best model, Akaike Information Criterion (AIC) values were employed. AIC is a valid method for evaluating model fit that penalizes superfluous complexity. A lower AIC value indicates a more robust model.

| **Model** | **AIC** | **BIC** |
|---|---|---|
| ANN | 618.0988 | 623.6494 |
| AAN | 622.4896 | 630.4072 |
| **AAA** | **544.3347** | **551.3699** |
| MAM | 558.9280 | 566.2565 |

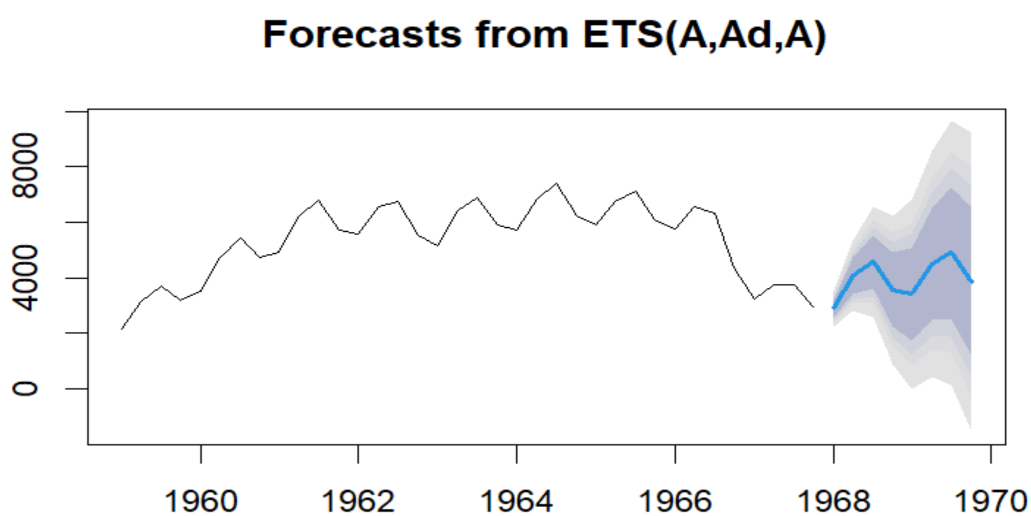
Among the models considered, the ETS(A,Ad,A) model came out with the lowest AIC value. This demonstrated its capacity to accurately capture additive trends, damped trends, and additive seasonal components. As Gardner (2006) pointed out, such models excel at managing dynamic datasets containing both short-term and long-term fluctuations.

Residual diagnostics validated the model's reliability, with residuals distributed randomly around zero, indicating that the ETS(A,Ad,A) model accurately described the data's underlying structure. Although this feature was not expressly mentioned, it is nevertheless a regular practice in predicting. The residuals also exhibited close normality, confirming the model's suitability for producing unbiased predictions.




**Forecasting Results**

Forecasts were visually represented using point estimates and prediction intervals at 80%, 90%, 95%, and 99% confidence levels to aid decision-making. This method offers a useful framework for comprehending future values while recognizing the inherent uncertainties. As the use of prediction intervals is critical for risk assessment because it incorporates uncertainty in projected outcomes.




The ETS(A, Ad, A) model's ability to capture both seasonal changes and long-term trends was especially impressive. The addition of a damped trend component improved the model's adaptability, allowing it to handle fluctuations in trend intensity. As Kourentzes, Petropoulos, and Trapero (2014) showed, adding structural components at multiple frequencies improves forecasting accuracy and reliability.

## ARIMA, ANALYSIS AND FORECASTING

The ARIMA methodology was chosen for its known effectiveness in time series forecasting, which balances simplicity and robust performance. This part includes assessing data trends, seasonality, and variations prior to selecting and confirming the best forecasting model.

Visualizations were used to thoroughly study the historical data in order to identify trends, recurring patterns, and volatility. Plotting the data revealed seasonal spikes and noticeable patterns that necessitated preprocessing for a more accurate analysis. The data was then refined using techniques such as differencing.

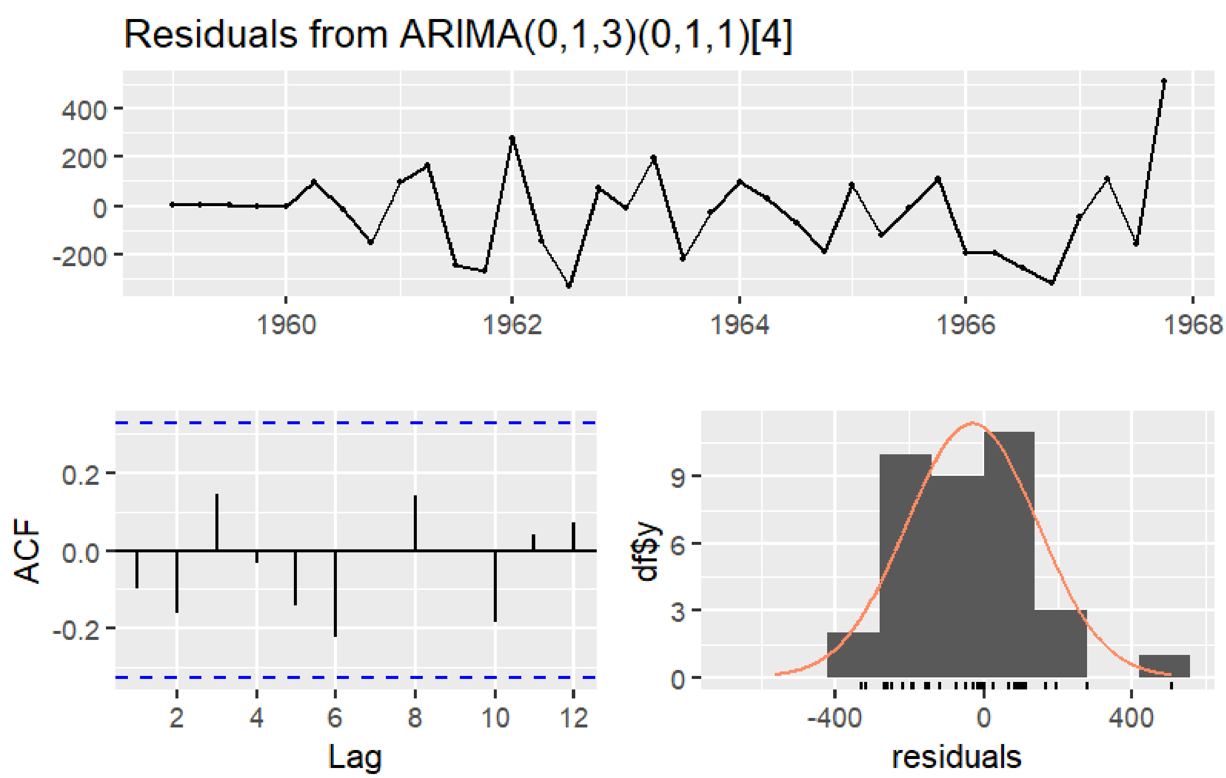
To prepare the data, first-order differencing was used to remove long-term trends, which improved the focus on relevant patterns. This procedure is consistent with the methodologies described by Kourentzes, Petropoulos, and Trapero (2014) for finding structural components. Additionally, seasonal differencing with a four-month lag addressed reoccurring quarterly trends, ensuring the dataset was suitable for ARIMA modeling.

Statistical tests were used to verify the preprocessed data's stationarity. The Augmented Dickey-Fuller (ADF) test revealed stationarity with a low p-value, which is compatible with the procedures discussed by Hyndman and Koehler (2006). Furthermore, the KPSS test verified stationarity with a high p-value, which is consistent with the robust data preparation strategies for forecasting outlined by Tashman (2000).

### Model Selection and Evaluation

Various ARIMA configurations for non-seasonal and seasonal components were examined to determine the best model for forecasting.

Models were evaluated using metrics such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). These criteria help to balance model complexity and goodness of fit, ensuring that the chosen model is neither underfitted nor overfitted.



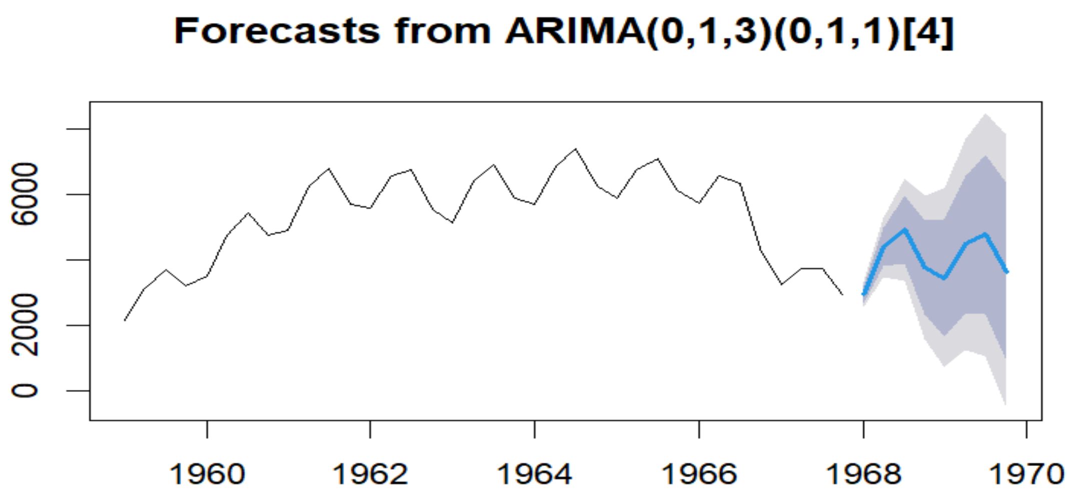
The ARIMA(0,1,3)(0,1,1)[4] model emerged as the best fit, reflecting both short-term dependencies and seasonal trends.

The residuals from each model were analysed for patterns and unpredictability. The absence of systematic errors in the residuals supported the model's dependability.

**Forecasting Results**

The validated model was used to provide forecasts for the next eight quarters. These predictions include both point estimates and prediction intervals, providing a thorough view of future job offer patterns.

1. Point Predictions: The forecasts provide particular figures for predicted job offers that reflect the overall trend in the data.
2. Prediction Intervals: By accounting for uncertainty, intervals provide a range of possible outcomes, which improves decision-making under changing market conditions.




The forecasts were presented using a time series graphic, which highlighted the expected changes with historical data. This gives stakeholders a clear grasp of expected labor market trends.

## BATCH FORECASTING

The goal of this section is to perform a thorough review of time series forecasting approaches, with a special emphasis on two often-used methods: ARIMA (Auto-Regressive Integrated Moving Average) and ETS (Exponential Smoothing State Space Model). Time series forecasting is an important method for predicting future values based on historical data, with applications in domains such as economics, business analytics, and supply chain management. Understanding and applying ARIMA and ETS models can help us enhance decision-making and operational efficiency in a variety of domains.

The purpose is to apply these forecasting approaches to a varied dataset containing 70 different time series. These time series may differ in their features, such as seasonality, trend, and noise, so it is critical to examine how ARIMA and ETS models handle different types of data. Both ARIMA and ETS have strengths and weaknesses. ARIMA is especially useful for time series with linear relationships, but ETS is noted for its ability to capture exponential smoothing patterns and is better suited to seasonal data (Hyndman & Khandakar, 2008). Understanding how these models behave in diverse circumstances will provide useful insights into their performance and applicability.

The analysis of error measurement metrics is an important component for determining the accuracy of forecasting models. Metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) will be used to assess ARIMA and ETS models' prediction ability across time series. These error measures are critical for establishing the dependability and robustness of forecasting models, as well as deciding which method produces the most accurate predictions for each type of time series (Hyndman and Koehler, 2006; Tashman, 2000). Clemen (1989) and Davydenko & Fildes (2013) underline the necessity of reliable error measurement in evaluating model performance and guiding future improvements.

Furthermore, the report contains a benchmarking part in which the performance of the ARIMA and ETS models is compared using these error metrics. Benchmarking different models can provide insights into which method is better suited to specific data features, providing for a more in-depth understanding of each model's strengths and limitations (Fildes & Petropoulos, 2015). The results of this study will also assist in guiding future time series forecasting decisions for a variety of applications, taking into account the trade-offs between model complexity and forecasting accuracy. Additionally, Petropoulos et al. (2014) highlight the necessity of selecting the appropriate forecasting model for the given data environment, which improves forecasting reliability and operational performance.

### Forecasting Methods

1. **Automatic ETS**: The ETS approach chooses the optimal model that fits the data depending on its specific properties using the ets() function. This technique is versatile since it can handle a variety of data sources, including trends and seasonality.

   Key advantages include:

- Flexibility to accommodate both basic and complex seasonal cycles.
- Capability to track trends throughout time.
- Adaptation to different degrees of data smoothness.

2. **Automatic ARIMA**: ARIMA is another way for automatically selecting the optimal forecasting model based on statistical criteria by using auto.arima() function. This shortened procedure ensures that the model can handle both short- and long-term patterns.

The major benefits include:

- Capable of capturing seasonal and non-seasonal trends.
- Adjusts for changes in the data over time.
- Selects the most accurate parameters using a data-driven process.

3. **Custom Model Selection Strategy:** To guarantee the best model is picked for each data series, a personalized strategy was utilized, including : Cross-validation which is a technique that checks the model on diverse data sets to ensure it performs well over time. In Error metrics models are compared using performance indicators to ensure we chose the most accurate one. Consistent Performance is also used; this technique focuses on selecting a model that performs well across multiple datasets.

This approach assures that the chosen model is the most dependable and accurate for the given data.

Automatic detection of outliers

Data points that depart from predicted patterns, known as outliers, can have a major impact on predicting model accuracy. To provide accurate forecasts, an automatic outlier detection method was included in the model selection. This is how it works:

- Outliers were identified by studying the residuals, which are the disparities between expected and actual data. Statistical tests and range analysis were used to identify these outliers.
- Outliers were found and either eliminated or corrected to avoid skewing the results. This ensured that the models were fitted with the most accurate data possible.
- By correcting outliers, we ensure that the chosen model can handle real-world data consistently, making forecasts more reliable. This phase is critical in picking a model that produces reliable results even in the presence of data anomalies.

## Evaluation Metrics

To ensure a thorough performance assessment, each model was examined using a variety of error metrics. The error metrics comprised the following:

- Root Mean Squared Error (RMSE): Determines the square root of the average squared difference between anticipated and actual data.

- Mean Absolute Error (MAE): Calculates the average of absolute errors, providing interpretability within the original data scale.

- The Mean Absolute Percentage Error (MAPE) expresses the average error as a percentage of the actual values, making it scale-independent.

The models were trained using historical data and validated with planning horizons of varied durations to imitate real-world decision-making situations.

## Benchmarking Methods

Benchmarking is critical for evaluating the accuracy and performance of forecasting models, allowing us to select the best model for a given time series dataset. In this study, benchmarking methods were utilized to assess the efficacy of six forecasting models: ARIMA, Damped ETS, ETS, Naive, Simple ETS, and Model Selection. Each model was assessed using performance metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), which provide a comprehensive picture of the model's prediction accuracy and robustness.

The models were evaluated using a single-time validation approach, which means they were trained on a subset of the dataset and then tested on the rest of the data to determine their forecast accuracy. This validation method allows for quick and efficient model evaluation, but it may not capture all of the variability in time series data. Further improvements, such as cross-validation or rolling-window validation, may be investigated for more robust results (Fildes & Petropoulos, 2015).

In the context of predicting time series data, various categories were employed in the model selection process to decide which model best fits specific sorts of data features. The categories included:

- **Micro:** Refers to small-scale datasets with fewer complex patterns, where models such as Naive or Simple ETS may be better suited for short-term prediction.

- **Macro:** Involves larger datasets with more pronounced seasonality and trends, necessitating the use of more complicated models like ARIMA or ETS to make reliable long-term predictions.

- **Demographic:** Datasets are segmented by demographic factors like age, geography, and so on, and more specific models, such as model selection, can be employed to account for differences in behavioural patterns among subgroups.

## Model Selection, Performance and Comparison

The selection of the optimal model varied according to particular error metrics:

- ARIMA is the best model in terms of RMSE.
- The best model based on MAE is Damped ETS.
- The best model based on MAPE is Naive.

| Model | Average RMSE | Average MAE | Average MAPE | Performance Summary |
|---|---|---|---|---|
| ARIMA | 523 | 453 | 11.2 | Ideal for stationary data and scenarios that require exact point forecasts. |
| Damped ETS | 533 | 449 | 11.9 | Effective for data with weak trends; fared well across most parameters, resulting in smoother projections where trends are less obvious. |

| | | | | |
|---|---|---|---|---|
| Model Selection | 540 | 455 | 11.5 | A hybrid strategy integrating several methods for model selection delivers a strong evaluation but requires additional validation. |
| Naïve | 526 | 452 | 11.1 | Simple baseline that works well for short-term forecasting but lacks sophistication when dealing with complex seasonal or trending data. |
| Simple ETS | 544 | 470 | 11.6 | Suitable for stable series but underperformed on series with pronounced trends. |

According to the average RMSE, MAE, and MAPE values shown in the table above, ARIMA is the most accurate forecasting model, with the lowest error rates across all metrics. While alternative models, such as Damped ETS, ETS, and Naive, yield acceptable results, ARIMA's ability to address both seasonal and non-seasonal components makes it the most dependable for the given dataset. The simple ETS model, while effective, has larger errors and may not be appropriate for data with complicated patterns and seasonality.

**<u>Planning Horizons</u>**

Planning horizons are an important consideration in practical forecasting applications because they set the timeframe for making predictions and influence the model's ability to reliably estimate future values. Forecasting horizons are divided into three categories: short-term, medium-term, and long-term, with each posing new issues for forecasting models. The ARIMA model was assessed over these varied horizons and consistently outperformed other models. ARIMA fared well for short-term forecasts, which are often concerned with current or near-future values, by incorporating recent patterns and seasonality in the data. As the forecasting horizon expanded to the medium term, ARIMA's ability to handle both non-seasonal and seasonal components continued to generate accurate forecasts, making it a reliable choice for forecasting in this timeframe (Hyndman and Khandakar, 2008).

The ARIMA model's most noticeable strength, however, was its superior performance in long-term forecasting. As the horizon widened, the data revealed more intricate seasonal patterns and long-term trends, necessitating a model capable of handling such intricacies. ARIMA succeeded in this area, efficiently capturing intricate seasonal changes and trends while also delivering credible forecasts over extended time periods. ARIMA's capacity to perform across multiple forecasting horizons makes it a strong and versatile model, especially for forecasting in contexts with significant trends and seasonality. It demonstrates the model's ability to adapt to multiple forms of data over varying timescales, delivering useful insights into future patterns even as complexity increases.

## CONCLUSION

### Limitations

1. While batch forecasting is extremely efficient for big datasets, it may fail to address non-stationary behaviour or data with quick changes, necessitating manual model adjustments to maintain accuracy.

2. Automated model selection systems, such as ARIMA and ETS, may not always choose the best model for individual datasets, resulting in poor outcomes in some circumstances.

3. Models such as Naive and Damped ETS are frequently insufficient for long-term forecasting, particularly when dealing with datasets with strong patterns or seasonality.

4. Models that rely significantly on past data may struggle to swiftly adjust to unexpected changes or shocks in data, limiting their efficacy for real-time or dynamic forecasting.

5. Simple methods, such as naive forecasting, might produce erroneous results for more complicated information, particularly when nuanced patterns must be caught.

6. Some models, such as ARIMA, require extensive data preprocessing (e.g., differencing) to attain stationarity, which can complicate and lengthen the modelling proces

7. More complicated models, such as ARIMA, may necessitate significant processing power, which can be a challenge for organizations with limited resources.

8. Relying on rolling windows validation may not be practical in all scenarios, particularly with big or highly changeable datasets, due to the significant processing overhead.

.

### Implications

1. To ensure prediction accuracy, managers must thoroughly assess the data's properties (e.g., seasonality, trends, and volatility) before picking an appropriate forecasting model.

2. When choosing a model, consider the trade-off between complexity and accuracy. Simpler models, such as Naive, may be useful for short-term forecasting, whereas ARIMA and ETS are better suited to more sophisticated, long-term projections.

3. Organizations must explore bespoke model selection procedures, such as cross-validation and error comparison, in order to tailor the forecasting process to individual data requirements.

4. While automated model selection is efficient, personal intervention is still required to verify that the chosen model is well-suited to changing data dynamics and business objectives.

5. Businesses must manage resources based on the computational and temporal demands of more complicated forecasting models so that they are not overburdened with unneeded processing.

6. The ideal forecasting model may differ based on the planning horizon. For example, ARIMA may excel in long-term forecasting, yet simpler models may be sufficient for short-term forecasting.

7. Continuous monitoring of predicting accuracy is required to ensure that models stay relevant when new data is made available. Performance measures should be monitored to determine when model updates are required.

8. Accurate forecasting models are critical for making educated decisions, budgeting resources, and conducting strategic company operations, all of which can boost growth and reduce risks. Managers should match forecasting approaches with company goals to maximize impact.

## REFERENCES


1. Clemen, Robert T. 1989. "Combining Forecasts: A Review and Annotated Bibliography." *International Journal of Forecasting* 5 (4): 559–83. https://doi.org/10.1016/0169-2070(89)90012-5.
2. Davydenko, Andrey, and Robert Fildes. 2013. "Measuring Forecasting Accuracy: The Case of Judgmental Adjustments to SKU-level Demand Forecasts." *International Journal of Forecasting* 29 (3): 510–22. https://doi.org/10.1016/j.ijforecast.2012.09.002.
3. Fildes, Robert, and Fotios Petropoulos. 2015. "Simple Versus Complex Selection Rules for Forecasting Many Time Series." *Journal of Business Research* 68 (8): 1692–1701. https://doi.org/10.1016/j.jbusres.2015.03.028.
4. Gardner, Everette S. 2006. "Exponential Smoothing: The State of the Art—Part II." *International Journal of Forecasting* 22 (4): 637–66. https://doi.org/10.1016/j.ijforecast.2006.03.005.
5. Hyndman, Rob J, and Yeasmin Khandakar. 2008. "Automatic Time Series Forecasting: The Forecast Package for R." *Journal of Statistical Software* 27 (3): 1–22. https://doi.org/10.18637/jss.v027.i03.
6. Hyndman, Rob J, and Anne B Koehler. 2006. "Another Look at Measures of Forecast Accuracy." *International Journal of Forecasting* 22 (4): 679–88. https://doi.org/10.1016/j.ijforecast.2006.03.001.
7. Hyndman, Rob J, Anne B Koehler, Ral Snyder, and Simone Grose. 2002. "A State Space Framework for Automatic Forecasting Using Exponential Smoothing Methods." *International Journal of Forecasting* 18 (3): 439–54. https://doi.org/10.1016/S0169-2070(01)00110-8.
8. Kourentzes, Nikolaos, Fotios Petropoulos, and Juan Ramon Trapero. 2014. "Improving Forecasting by Estimating Time Series Structural Components Across Multiple Frequencies." *International Journal of Forecasting* 30 (2): 291–302. https://doi.org/10.1016/j.ijforecast.2013.09.006.
9. Petropoulos, Fotios, Spyros Makridakis, Vasilios Assimakopoulos, and Konstantinos Nikolopoulos. 2014. "'Horses for Courses' in Demand Forecasting." *European Journal of Operational Research* 237: 152–63. https://doi.org/10.1016/j.ejor.2014.02.036.
10. Tashman, Leonard J. 2000. "Out-of-Sample Tests of Forecasting Accuracy: An Analysis and Review." *International Journal of Forecasting* 16 (4): 437–50. https://doi.org/10.1016/S0169-2070(00)00065-0.