Guidelines for a 48”x 36” poster

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Abstract

The accurate prediction of electricity consumption is of paramount importance in today's energy-intensive world. Electricity serves as the backbone of modern societies, powering industries, businesses, households, and various essential services. The effective forecasting of electricity consumption not only aids in optimal energy resource management, for instance, but also influences policy decisions, infrastructure planning, and economic stability. Specifically, (1) accurate predictions enable optimal **allocation of energy resource**s, including fossil fuels and renewable sources, helping utility companies meet demand efficiently. (2) Long-term electricity consumption forecasts aid in **planning and developing a robust energy infrastructure** to accommodate future growth. (3) Reliable forecasting supports the integration of renewable energy sources, promoting sustainable practices and reducing carbon emissions. (4) Businesses rely heavily on electricity, and precise forecasts assist in **managing production, operations, and budgeting effectively**.

In this study, we focus on forecasting the monthly retail sales of electricity in the commercial sector in the United States. We will compare the performance of the Auto ARIMA, ETS, and Seasonal Naive models, aiming to identify the most suitable approach for accurate and reliable predictions. Additionally, we will investigate the potential benefits of an ensemble model, which combines the strengths of individual models, to achieve enhanced forecasting accuracy.

The findings suggest that while the individual models have their strengths and weaknesses, the Ensemble model offers a balanced approach by combining the strengths of each model. However, further investigation and fine-tuning are required to enhance its performance. Overall, this study provides valuable insights into time series forecasting and the potential benefits of ensembling different forecasting techniques for improved prediction accuracy.

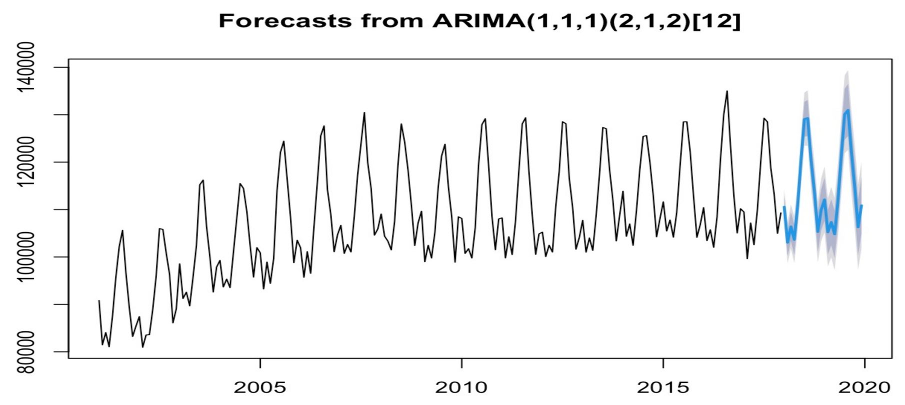
Introduction & Significance

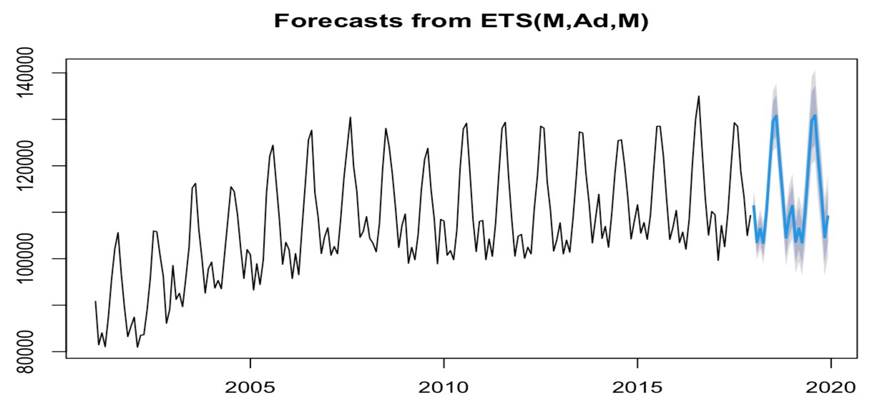
Introduction
Electricity consumption plays a crucial role in the economic growth and development of a country, with the commercial sector being a major consumer. Accurate forecasting of electricity sales in the commercial sector is essential for effective energy planning, resource allocation, and decision-making. Time series forecasting techniques are widely used to predict future electricity consumption patterns based on historical data.
In this study, we focus on time series forecasting of the monthly retail sales of electricity in the United States' commercial sector. The dataset is obtained from the U.S. Energy Information Administration and covers a significant period of historical data. We aim to develop and compare different forecasting models to identify the most accurate and reliable method for predicting future electricity sales.

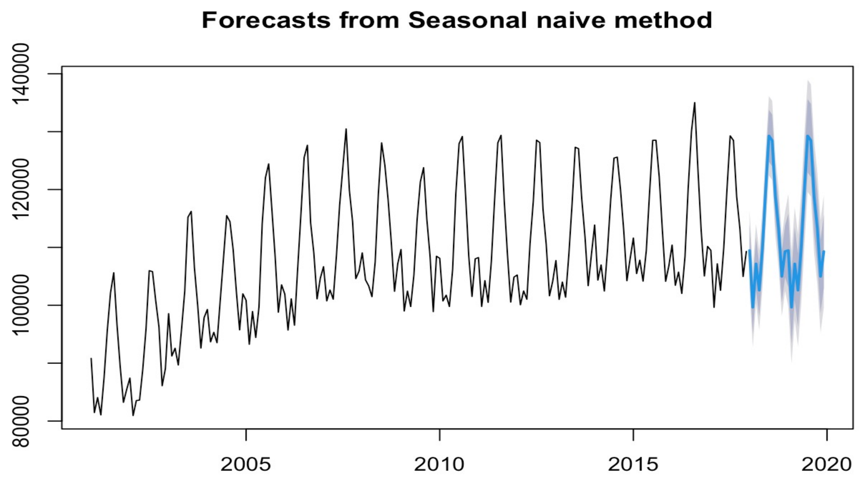
Significance
1. Energy Planning and Management: Accurate forecasting of electricity consumption in the commercial sector helps utility companies and policymakers plan and manage energy resources efficiently. It enables them to estimate future electricity demand, leading to optimal power generation and distribution.
2. Cost Optimization: Accurate forecasts allow businesses and utility companies to anticipate peak demand periods, enabling them to optimize their energy procurement and avoid unnecessary costs associated with energy surges.

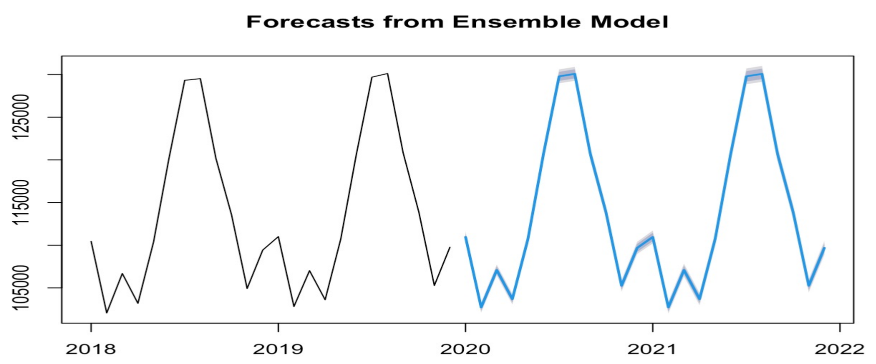
Methods

- Data is collected from the U.S. Energy Information Administration, comprising monthly retail electricity sales in the commercial sector of the United States.
- The dataset is preprocessed and transformed into a time series format.
- The time series data is visualized using ggplot2 and ggfortify packages to understand its patterns, trends, and seasonality. Seasonal decomposition is performed using feasts to identify any underlying components.
- Three time series forecasting models are selected: Auto ARIMA, ETS, and Seasonal Naive.
- The models are trained on the first four years of data.
- Model evaluation is performed using accuracy metrics and the Ljung-Box test.
- An ensemble model is created by averaging the forecasts from the three models.
- Forecasts are generated for the next 24 months.
- Model performance is compared, and practical implications are discussed.









Results

1. The accuracy for Arima model forecasts

```
##                      ME     RMSE      MAE         MPE     MAPE      MASE
## Training set -141.59070 1774.039 1317.361 -0.14277668 1.214851 0.5046274
## Test set       97.20485 2485.310 1875.670 -0.01517716 1.636782 0.7184928
##                    ACF1 Theil's U
## Training set -0.01362682        NA
## Test set      0.26791122 0.2825577
```

2. The accuracy for ETS forecasts

```
##                     ME     RMSE      MAE         MPE     MAPE      MASE
## Training set -17.21591 1738.712 1348.679 -0.03976572 1.258415 0.5166238
## Test set     524.14577 1951.011 1544.617  0.39796190 1.338081 0.5916801
##                    ACF1 Theil's U
## Training set  0.08779091        NA
## Test set     -0.05325528 0.2209316
```

3. The accuracy for SNAIVE forecasts

```
##                    ME     RMSE      MAE      MPE     MAPE      MASE      ACF1
## Training set 1405.308 3492.199 2610.562 1.337117 2.430320 1.0000000 0.6290155
## Test set     1535.667 2757.895 2298.651 1.276381 1.969668 0.8805197 0.2553548
##              Theil's U
## Training set        NA
## Test set     0.2968618
```

4. The accuracy for Ensemble models forecasts

```
##                      ME      RMSE       MAE         MPE     MAPE       MASE
## Training set   51.79243  208.9028  165.9318  0.04478147 0.149904  0.3643467
## Test set     -4777.07568 6237.4809 4887.8617 -4.61233330 4.701962 10.7325797
##                   ACF1 Theil's U
## Training set 0.6573313        NA
## Test set     0.5898488 0.7833525
```

The ETS model has the lowest RMSE, indicating that it has the smallest average forecasting error among the individual models.

The ETS model also has the lowest MAPE, indicating that, on average, its percentage forecasting errors are the smallest compared to the actual values.

The ETS model has the lowest MASE, suggesting that it performs better in terms of scale accuracy compared to the other models.

The seasonal naive model (Snaive) performs better than the ARIMA model in terms of RMSE, MAPE, and MASE.

The ensemble model, surprisingly, performs the worst among all models, with significantly higher RMSE, MAPE, and MASE.

Based on the test set evaluation, the ETS model appears to be the most accurate in forecasting the monthly retail sales of electricity in the commercial sector for the United States. However, it's essential to consider the specific forecasting requirements and the data characteristics when selecting the best model for practical applications.
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Discussion

The Auto ARIMA model showed reasonably good forecasting performance, and its automated approach in determining the optimal order of differencing and seasonal differencing makes it highly practical

The ETS model demonstrated the best forecasting accuracy among the individual models on this analysis. It successfully captured the underlying error, trend, and seasonal components present in the data, making it suitable for time series with strong seasonal patterns.

The Seasonal Naive model serves as a simple and intuitive benchmark for seasonal time series forecasting. While its forecasting accuracy is not as high as the ETS model, it remains valuable as a reference point for evaluating the performance of more complex models. The Snaive model's ease of implementation and straightforward interpretation make it useful in scenarios where a quick and basic forecast is sufficient.

The Ensemble model aimed to combine the forecasts from the three individual models to leverage their strengths. However, in this specific analysis, the Ensemble model did not demonstrate significant improvement over the individual models, potentially because the ETS model already provided highly accurate forecasts. The utility of the Ensemble model lies in its potential to enhance forecast accuracy in cases where different models complement each other, providing more robust predictions and reducing reliance on a single model's performance.

Conclusion

Among the individual models, the ETS model demonstrated the best forecasting performance, with the lowest Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Scaled Error (MASE). The ETS model's superior performance suggests that it is well-suited for forecasting electricity retail sales in the commercial sector. The Ensemble model, which combined forecasts from multiple models, did not outperform the individual models and showed higher forecast errors, indicating that the ensemble approach might not be appropriate for this specific time series.

References

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