Impact of Renewable Energy Adoption on Business Operations in Colorado

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Executive Summary:

The analysis focused on the impact of adopting renewable energy on business operations in Colorado. Key findings revealed a clear seasonal pattern in wind energy production, highlighting peak electricity generation in March and a decline in August. This pattern suggests that businesses utilizing wind power should align their production plans accordingly. The evaluation of forecast accuracy indicated that the seasonal Holt-Winters model outperformed the seasonal ARIMA model, making it a suitable choice for future predictions. And we used GLM model to find factors that are influential to the total percentage of renewable energy.

Key Findings:

- Wind energy production in Colorado exhibits a clear seasonal pattern, with peak electricity generation in March and a decline in August.
- Businesses utilizing wind power should align their production plans with the seasonal pattern to optimize operations.
- The seasonal Holt-Winters model demonstrated superior forecast accuracy compared to the seasonal ARIMA model.

Conclusion:

The analysis highlighted the importance of adopting renewable energy in Colorado and its impact on business operations. By understanding the seasonal pattern in wind energy production, businesses can strategically plan their operations. The evaluation results favored the seasonal Holt-Winters model for accurate forecasting. Factors influencing the net renewable energy generation rate included total electricity generation for industrial purposes, electricity generation from sources other than solar, solar power generation, coal prices, population growth, and coal consumption for electricity generation.

1. Introduction

Renewable energy is increasingly significant in various industries, such as transportation, heating, and cooling, and its adoption is transforming business operations in Colorado. The analysis focused on understanding the impact of adopting renewable energy on business operations. The results revealed that wind turbines produce the greatest amount of electricity during the months around March, while the lowest energy generation occurs around August. Consequently, businesses that rely on wind power should adjust their production plans accordingly, with higher workloads during the winter months and lower workloads during the summer.

2. Data

I utilized data from the U.S. Energy Information Administration Website (https://www.eia.gov/state/?sid=CO) for my analysis. The dataset was carefully preprocessed by removing irrelevant columns and rows. The resulting data is clean and well-organized, free of any missing values. Figure 1 is the visualization of data.

2.1 Visualization

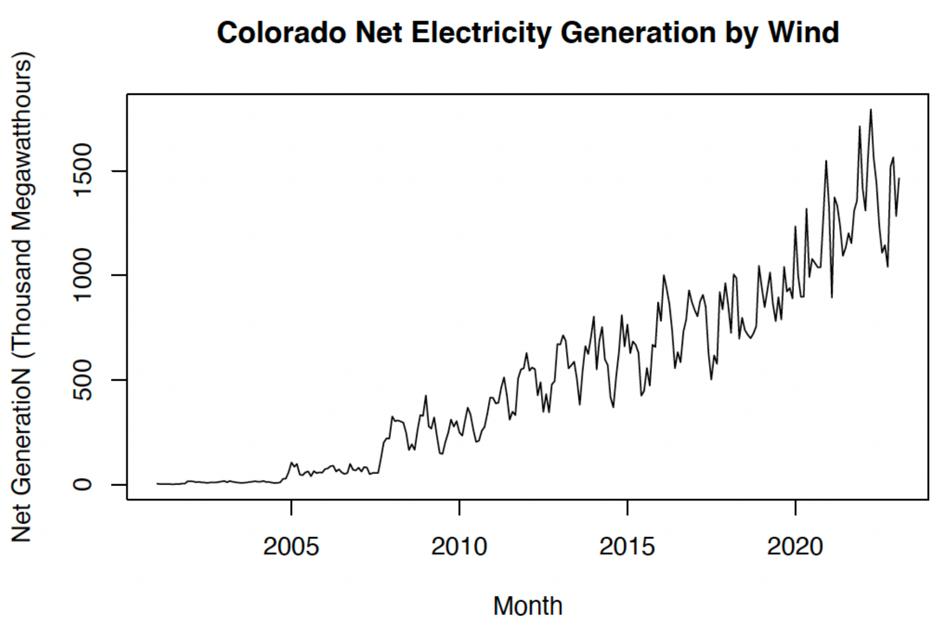

Figure 1. Colorado Net Energy Generation by Wind

After examining the data, it is noticeable that the time series displays a non-stationary nature with a continuous upward trend starting from 2008. Moreover, a noticeable seasonal pattern is evident from the plotted data. To validate the presence of both trend and seasonality, I generated a decomposition chart (see Figure 2). The decomposition chart clearly illustrates the prominent upward trend and the recurring seasonal pattern in the data. These findings emphasize the importance of addressing the trend and seasonality components when modeling and analyzing the time series data.

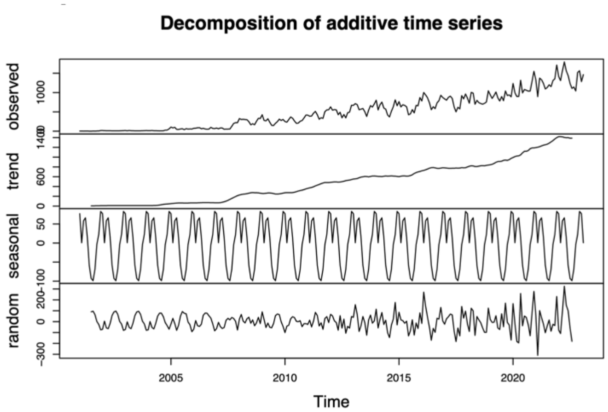

Figure 2. Decomposition Graph

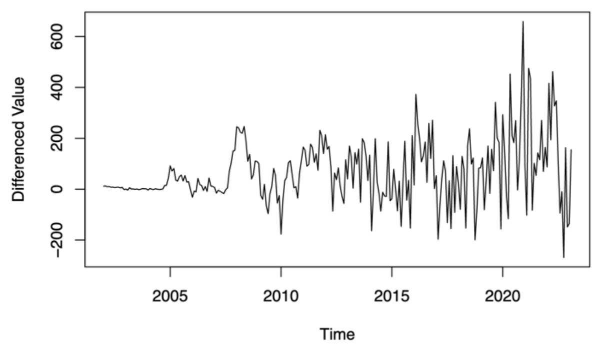

Figure 3. Differenced Time Series Graph

2.2 Differencing data

To train and select the most appropriate model for my analysis, I initially applied differencing to the data, resulting in a stationary time series (refer to Figure 3). To validate the stationarity of the differenced data, I conducted the Dickey-Fuller test. The obtained p-value of 0.01 indicates statistical significance, confirming that the differenced data is indeed stationary. This ensures that the subsequent modeling and analysis can be conducted reliably.

3. Model

3.1 Arima

To predict future values of the time series, I initially employed a seasonal ARIMA model. This model-based approach involves fitting an ARIMA model to the data and utilizing it for forecasting. By examining the ACF and PACF plots (refer to Figure 4), it appears reasonable to consider a lower-order ARMA or AR model. The PACF demonstrates a cutoff at lag 2, gradually decaying to 0, while the ACF exhibits a clear trend that eventually decays to 0. However, despite the early cutoff, the significance of the lag emerges again around the 13th month, indicating a periodic pattern characteristic of seasonality with a period of 12.

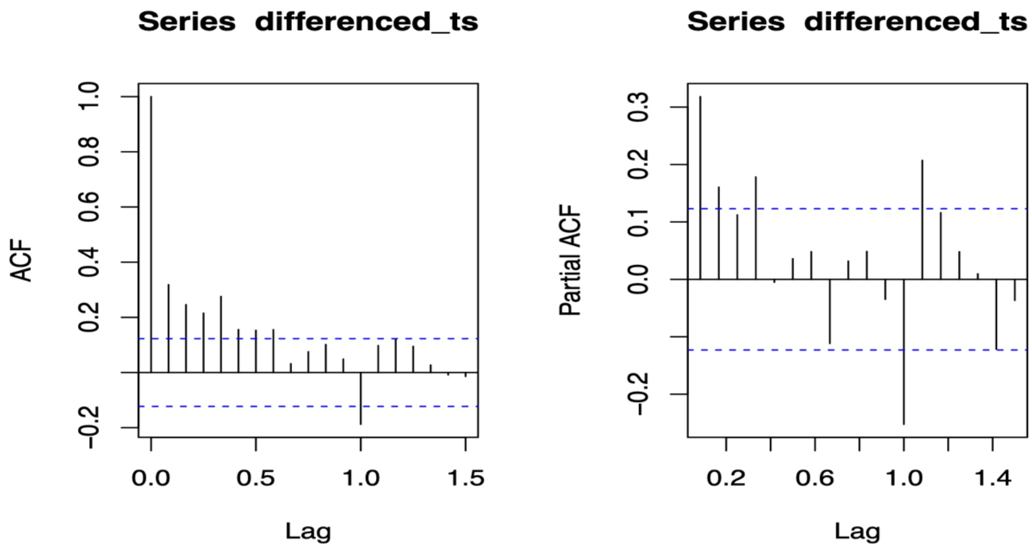

Figure 4. ACF and PACF

With my hypothesis that lower order of ARMA or AR model would fit the best, I tried several models and I pick the model with the lowest AIC score (see table 1) which is ARMA (2,1,0) x SARMA (1,0,0)12 model. And Figure 5 is the time series forecast of the chosen model.

```
##                     Model   AIC
## 1    (1, 0, 1)x(1, 0, 0) 23.64
## 2    (1, 1, 1)x(1, 0, 0) 11.64
## 3    (1, 1, 1)x(1, 1, 0) 37.80
## 4    (1, 1, 1)x(1, 0, 1) 13.88
## 5 -> (2, 1, 0)x(1, 0, 0) 11.19
## 6    (0, 1, 2)x(1, 0, 0) 12.06
```

Table 1. Comparison Table

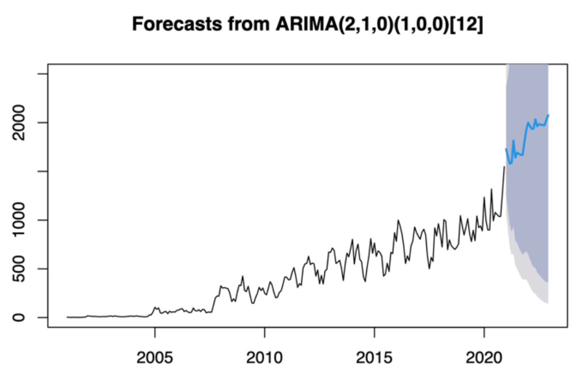

Figure 5. Time Series Forecast for The Chosen Model

Upon observing the diagnostic plots (see Fig.6), it is evident that the model performs exceptionally well. The residuals exhibit a random pattern with no discernible trends or patterns, indicating that the model adequately captures the underlying information in the data. The mean of the residuals is centered around zero, suggesting an unbiased model. The spread of the residuals remains consistent over time, indicating appropriate variance estimation. Additionally, the autocorrelation of the residuals is close to zero for all lags, suggesting that the model effectively captures the serial dependence in the data. Overall, the diagnostic plots demonstrate a robust and reliable model fit.

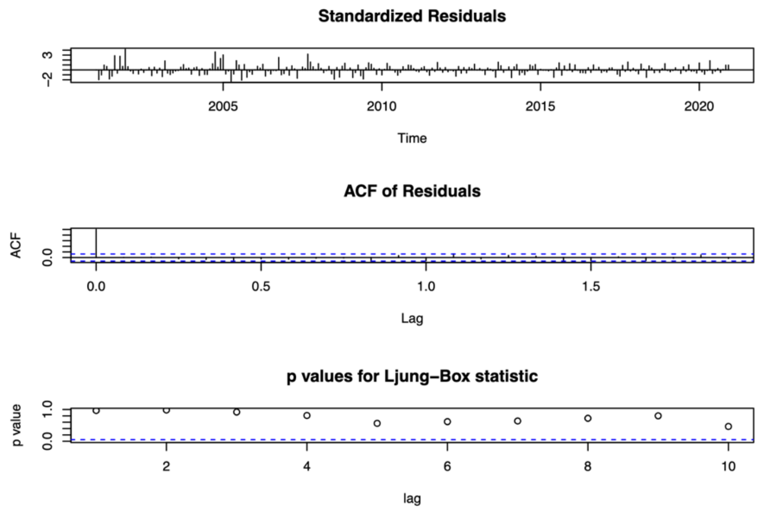

Figure 6. Diagnostic Plot

3.2 Holt-Winters Model

Besides the Arima model there is another model called Holt-Winters model. The Holt-Winters model, also known as triple exponential smoothing, is a time series forecasting method that takes into account trend, seasonality, and level components of the data. It uses exponential smoothing techniques to make predictions based on past observations and adjusts for both trend and seasonality. Given that the seasonal pattern of the data has constant increasing rate throughout the observed range, I employed the multiplicative version of the Holt-Winters model (see Figure 7.). The resulting forecast appears sensible and aligns well with the underlying patterns in the data.

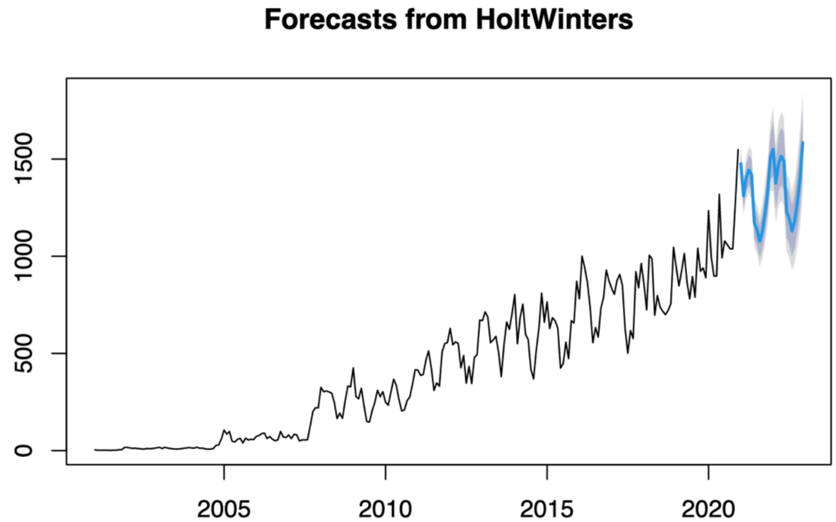

Figure 7. Time Series Forecast with Holt-Winters Model

3.3 Evaluation

To evaluate the performance of the two models, I reserved 24 observations, equivalent to 10% of the total data, as a test dataset. It was important to retain enough seasonal patterns in the test sample for accurate assessment. I employed metrics such as root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) to measure the forecast accuracy. Based on these metrics, the seasonal Holt-Winters model outperformed the seasonal ARIMA model, as indicated in Table 2.

```
##              Name      MAE     RMSE     MAPE
## 1           ARIMA 519.0775 557.9404 42.02811
## 2 Holt-Winters 115.3008 150.9800  9.13792
```

Table 2. MAE & RMSE & MAPE

4. Appling the Holt-Winters model and Findings

The time series analysis of renewable energy generated from wind over the past 20 years in Colorado reveals a notable pattern, with the lowest energy generation consistently occurring around August each year and the highest point reached around March. This discovery holds significant implications for understanding the dynamics of wind energy production and can inform strategic decision-making for renewable energy planning and management. (See Fig.8)

During the months of lower wind energy generation, such as August, businesses may face a relatively lower availability of renewable energy. To compensate for this potential energy shortfall, businesses can implement energy management practices and technologies to optimize their energy consumption. This could involve implementing energy-efficient measures, such as upgrading equipment, improving insulation, and utilizing smart energy management systems to minimize energy waste.

On the other hand, during the months of higher wind energy generation, particularly around April, businesses can take advantage of the increased availability of renewable energy. They can align their energy-intensive operations, such as manufacturing processes or equipment usage, to coincide with this period. By leveraging the abundance of renewable energy, businesses can reduce their reliance on non-renewable sources and lower their overall carbon footprint.

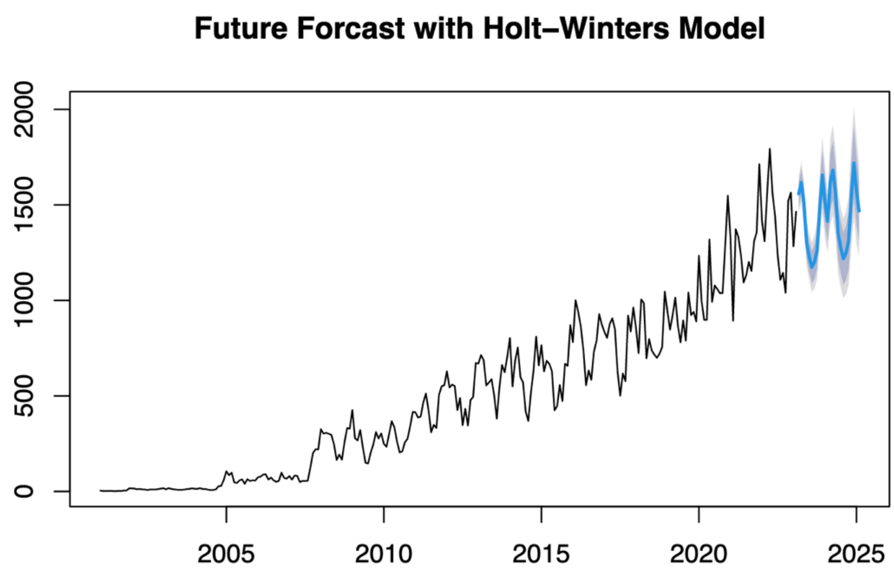

Figure 8. Future Forecast with Holt-Winters Model

5. Using GLM Model to Find Possible Influential Factors

The provided output shows the results of a linear regression model that predicts the net renewable energy generation rate over the total fuel generated in Colorado (refer to Table 3). The model includes several predictor variables: All_fuel, Other_renewable, Solar, Coal_Price, COPOP, and Coal. The coefficients, standard errors, t-values, and p-values are reported for each predictor. Analyzing the results, we can observe that several predictors are statistically significant in explaining the variation in the net renewable energy generation rate:

1. All_fuel: The negative coefficient (-0.3562) indicates that as the total electricity generation for industrial purposes increases, the net renewable energy generation rate decreases. This result suggests that a higher reliance on non-renewable sources of electricity in industrial sectors reduces the proportion of renewable energy generation.
2. Other_renewable: The positive coefficient (11.9529) suggests that an increase in electricity generation from sources other than solar leads to a higher net renewable energy generation rate. This finding highlights the importance of diversifying the renewable energy portfolio beyond solar power.
3. Solar: The positive coefficient (4.5727) implies that an increase in electricity generation from solar sources is associated with a higher net renewable energy generation rate. This result aligns with the well-known notion that solar power contributes significantly to renewable energy generation.
4. Coal_Price: The positive coefficient (0.0534) indicates that an increase in the price of coal per ton leads to a higher net renewable energy generation rate. This finding suggests that higher coal prices incentivize a shift toward renewable energy sources, potentially due to economic factors or policies promoting clean energy.
5. COPOP: The positive coefficient (0.0019) suggests that an increase in Colorado's population (in thousands) leads to a higher net renewable energy generation rate. This result implies that as the population grows, there is an increased demand for renewable energy, leading to a higher proportion of renewable energy generation.
6. Coal: The negative coefficient (-0.0008) implies that an increase in coal consumption for electricity generation (in tons) is associated with a lower net renewable energy generation rate. This finding suggests that a higher reliance on coal hampers the generation of renewable energy, potentially due to its environmental impact and carbon emissions.

```
Call:
glm(formula = Percentage ~ All_fuel + Other_renewable + Solar +
    Coal_Price + COPOP + Coal, data = df)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.1020  -0.5464  -0.0809   0.6293   3.2088

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)     -9.2471962  2.9246609  -3.162 0.001850 **
All_fuel        -0.3374723  0.0206617 -16.333  < 2e-16 ***
Other_renewable 14.4871271  0.7988573  18.135  < 2e-16 ***
Solar            4.5426205  0.1915770  23.712  < 2e-16 ***
Coal_Price       0.0273798  0.0078409   3.492 0.000608 ***
COPOP            0.0024023  0.0005118   4.694  5.4e-06 ***
Coal            -0.0003748  0.0002184  -1.716 0.087869 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.9031469)

    Null deviance: 1990.70  on 180  degrees of freedom
Residual deviance:  157.15  on 174  degrees of freedom
AIC: 504.08

Number of Fisher Scoring iterations: 2
```

Table 3. The Summary of The GLM Model

6. Conclusion

In conclusion, this analysis aimed to understand the impact of adopting renewable energy on business energy consumption patterns in Colorado. The study revealed distinct seasonal patterns in wind energy generation, with lower levels in August and higher levels in March. The Holt-Winters model outperformed the seasonal ARIMA model in forecasting, considering trend, seasonality, and level components. Factors influencing the net renewable energy generation rate included total electricity generation for industrial purposes, electricity generation from sources other than solar, solar power generation, coal prices, population growth, and coal consumption for electricity generation. These findings emphasize the importance of diversifying renewable energy sources, reducing reliance on non-renewable fuels, and implementing energy-efficient practices to optimize business energy consumption and promote sustainable growth in Colorado's renewable energy sector.

Reference:

1. https://www.nationalgrid.com/stories/energy-explained/what-are-different-types-renewable-energy

2. https://www.energyoutreach.org/

3. https://www.critterguard.org/blogs/articles/4-ways-businesses-can-benefit-from-renewable-energy-sources#:~:text=Reducing%20monthly%20energy%20costs%20is,panels%20to%20harness%20solar%20energy.