AUSTRIA'S WEATHER PREDICTION USING ARIMA/SARIMA MODEL

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Nguyen Phan Hong Ngoc – Research Analyst

Nguyen Phan Hong Ngoc – Research Analyst

PART I – FORECASTING THE TEMPERATURE
(COUNTRY: AUSTRIA)

1. INTRODUCTION

a. Austria's weather condition summary

As a part of European continent, Austria owns a central European transitional climatic zone which is dramatically influenced by Alps and named as "land of lake". Weather conditions across the nation earn low to moderate variation. Northern and Eastern side low land is specified as Pannonian climate, mean air temperature is recorded above 19°C in July and moderate precipitation, roughly 800 mm yearly. Western Austria feels the heat of Atlantic weather condition more apparently with moderately warm winter and comfortable summer; hence this side of the country is blissfully in less extreme climate. This area also records heavy rainfall. Austria orographic background also favors for Alpine climatic zone where temperature could change drastically and swiftly. This mountainous weather zone usually has colder winters compared to the lower land since temperature change varies along with altitude level. In sharp, this climatic diversity flourishes the development of flora and fauna (Austrian Embassy n.d.; George et.al 2023; World Bank n.d.).

January's temperature would shrink to become the coldest month. Warmth would rise in February and reach its peak in July as well as summertime. Additionally, April and October are cool, sometimes freezing with sudden snowfalls in April brought up by northerly winds (Climates to Travel 2020). Because of the mentioned diverse weather conditions impacted by geographical elements, the range between maximum and minimum degrees is wide with the average temperature recently calculated at 7,43°C (World Bank n.d.).

Regarding other environmental factors, sunshine duration per day has positive linkage with air temperature pattern. While the opposite is true to relative humidity. As proof, July peaks with roughly 9 hour-daytime and plunges under 70% of humidity ascertaining mild summertime here (World Data n.d.).

b. Importance of air temperature monitor

Besides the dependence of other meteorological variables on air temperature, livestock breeding, agriculture industry, every entity within the ecosystem as well as human well-being are also impacted; thus, air temperature has always been monitored strictly as an important weather variable (EEA 2022; Lou et.al 2019). Monitoring temperature to timely recognize and forecast any noticeable change in degrees because it determines the modification in ecosystem services, carbon storage or crop production could be listed, more severe level of higher degrees could naturally prompt droughts and other disasters on the large scale (EEA 2022).

c. Research objective

This paper navigates towards the analysis of monthly mean temperature of Austria during 1991-2020 period. Additionally, learning about data behavior via time series plot and relevant method would support the analysis with the fitted ARIMA/SARIMA model that would be utilized for mean temperature forecast next 10 years.

2. DESCRIPTIVE STATISTICS AND RELEVANT CHARTS

a. Descriptive measures (Central Tendency and Variance)

DESCRIPTIVE MEASURES	
Mean	7,25
Median	7,05
Max	19,20
Min	-6,00
1st Quartile	0,80
3rd Quartile	13,63
Standard Deviation	6,98

Figure 1. **Descriptive Measures of Austria's Mean Temperature 1991-2020 (Unit: °C).**

Austria Mean temperature during 1991-2020 period is 7,25°C whereas the Median is roughly alike but lower at 7,05°C, hereby implying a very modest tendency of positively skewed distribution in mean temperature data, merely normal distribution (openstax n.d.). Therefore, this indicates the weather would be recorded more values over 7,25°C among 360 observations. As previously introduced, the range between maximum and minimum value is wide due to climatic diversity, 25,2°C. However, the largest degree, 19,20°C is not compatible to real life recorded data. Because during summertime, the temperature hits ~35°C in July (Austria Embassy n.d.). Henceforth, this dataset could be assumingly recorded in Northern and Eastern low land region of Austria.

The dataset detects zero outlier in accordance with the Box-and-whisker Plot (Figure 2) justifying the Standard Deviation that be close to Mean value. The variation over period without extreme value (Figure 3) also strengthens the assumption. Furthermore, dividing the Standard Deviation to Mean, Coefficient of Variation (CoV) is resulted as follows:

$$CoV = \frac{SD}{Mean} = \frac{6{,}98}{7{,}25} \approx 0{,}96 < 1$$

CoV measures the ratio between Standard Deviation and the Mean to specify the variability and data dispersion around the Mean (Gordon 2021). The ratio equates approximately 0,96 implying typical low-level relative variability intensity (Zach 2021).

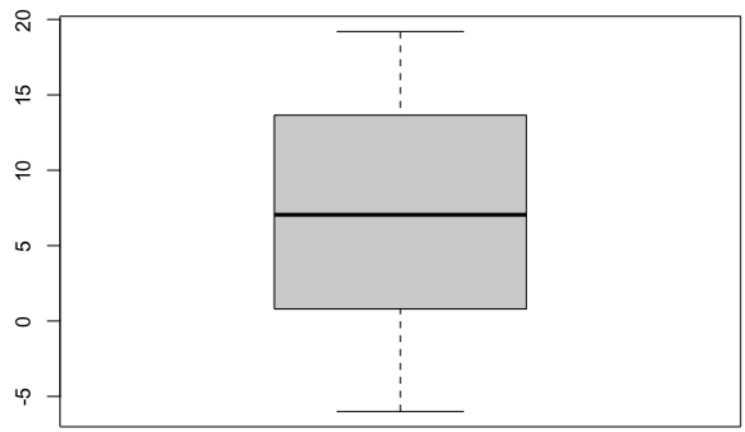


Figure 2. **Box and Whisker Plot of Austria's Mean Temperature 1991-2020 (Unit: °C).**

b. Time series plot and ACF examination

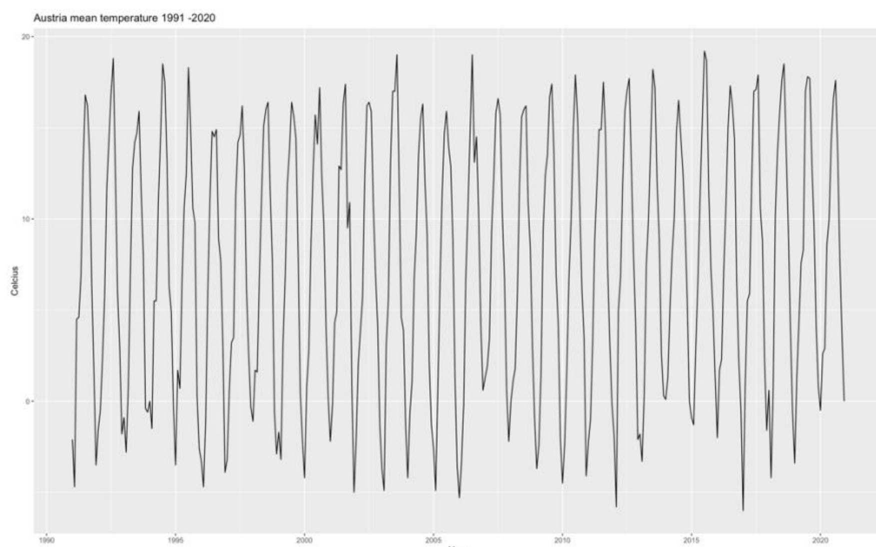


Figure 3. **Time series plot of Austria's Mean Temperature 1991-2020 (Unit: °C).**

On the one hand, the plot of Austria's Mean Temperature illustrates no clear trend with a few recognizable seasonality behaviors. Moreover, outlier does not appear during the plotted period.

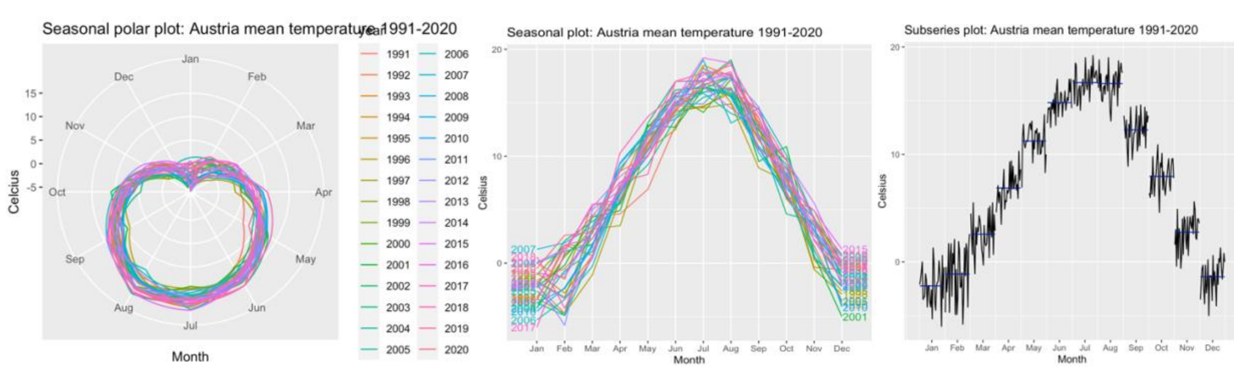


Figure 4. **Seasonal plot Austria's Mean Temperature 1991-2020 (Unit: °C).**
(4.1. Polar plot; 4.2. Seasonal plot; 4.3. Subseries Plot)

Looking into Figure 4.1, the seasonal polar plot indicates the seasonality when the temperature shrinks the bottom in January and climbs back month afterwards until summertime, July is repeatedly the warmest month. Degrees start to reduce when it comes to Autumn and Winter (September to December). Subseries plot (Figure 4.3) ascertains the underlying seasonality in Austria mean temperature with similar data behavior. Therefore, the seasonality is transparent stating the non-stationary data which needs differencing methodology to stabilize the mean. Additionally, the variation shows limited and obscured proportionally change over the level of series, mathematical transformation is redundant and unnecessary.

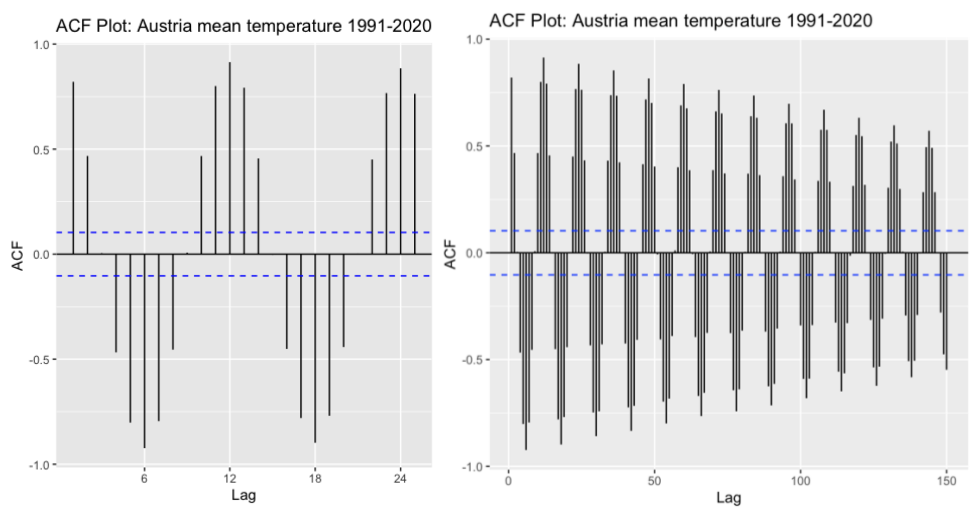


Figure 5. **ACF plot of Austria's Mean Temperature 1991-2020**
(5.1: 24-lagged plot; 5.2. 150-lagged plot)

Moreover, ACF plot with 24 lags and 150 lags emphasizes the seasonality pattern through illustrating the linkage between lagged values and time series. Moreover, every lag spikes over the blue line manifesting the non-stationary dataset since the data is not white noise. The 2 plots both have their peaks 12 periods apart. Henceforth, the data is proved to be non-stationary solidly.

In terms of forecasting issues in case time series plot would be used, seasonality or other underlying component could be major elements that might manipulate or reduce the forecasting accuracy. As seasonality would generate period swings in statistics and data behavior hereby yielding inaccurate forecasting results (Majaski 2022). Another limitation of time series forecasting application is its efficiency in long-term projection. As proof, time series only shows low errors in short-term forecasts such as the weather tomorrow might be alike today not next month (Jha et.al 2016). Restricted input data quantity, mutually independent character across variables could be considered as hurdles when applying time series prediction; thus, these 2 issues are main property and foremost challenges of time series data (Plummer 2000).

Machine learning is capable of tackling some of the mentioned difficulties. To seasonal time series, difference approach would help to stabilize the mean over time to prompt seasonal stationary time series and be ready for ARIMA/SARIMA forecasting model, an alternative that could be considered for projection (Plummer 2000).

3. MODEL SELECTION

a. Dataset transformation

Austria's Mean Temperature from 1991-2020 dataset has firmly recognized seasonality through plots in the previous part, hence, seasonally differencing is required to prompt seasonal stationary data. And as discussed, the variation shows no clear trend (upward or downward) over the periodical series, mathematical transformation such as Box Cox or logarithm unlikely to work well for further forecasting model.

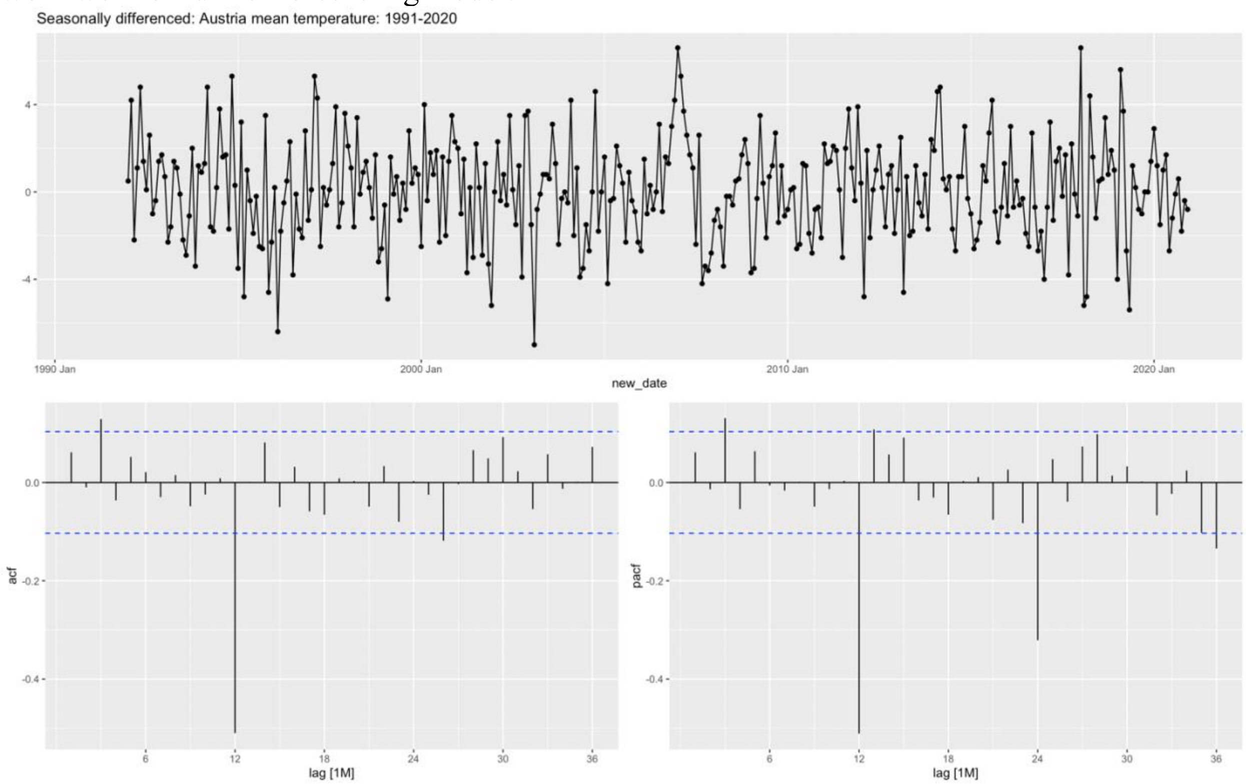


Figure 6. **Seasonally differenced plot of Austria's Mean Temperature 1991-2020.**

After first seasonal difference, the data achieve stationary immediately with seasonality pattern is swept away compared to Figure 5 (before transformation). The KPSS test after first difference results p-value at 0,1 (10%) which is higher than 0,05 (5%) to be verified as a stationary data (Prabhakaran 2019).

b. The most suitable ARIMA/SARIMA model

Best fitted SARIMA model depends on ACF and PACF plot to determine models' component (Figure 6). Firstly, seasonal components would illustrate seasonal MA/Q (1) thanks to spike at lag 12 of ACF plot, while seasonal AR/P (0) is recommended since seasonal lags at spike 12, 24, 36 illustrate exponential decay in PACF plot, seasonal difference D (1) as the dataset has applied one-time seasonal differencing as mentioned. On the other hand, non-seasonal MA/q (3) as the spike at lag 3 exceeds over the lag in range of non-seasonal period, the result is true to non-seasonal AR/p (3). Hence, we would initiate with **ARIMA (3,0,3)(0,1,1)$_{12}$** model.

model	sigma2	log_lik	AIC	AICc	BIC
arima303011	2.59	-674.	1363.	**1364.**	1394.
auto	2.72	-676.	1365.	1365.	1388.
arima300011	2.73	-678.	1366.	1366.	1385.
arima003011	2.75	-678.	1367.	1367.	1386.

Table 1. **Possible SARIMA models' criteria**

Model	RMSE
arima300011	1.62
arima003011	1.62
arima303011	1.57
auto	**1.61**

Table 2. **RMSE test for SARIMA model selection**

Automatically modeled ARIMA $(3,0,0)(0,1,2)_{12}$ is different from the initiative model. However, our former model **ARIMA $(3,0,3)(0,1,1)_{12}$** satisfies the lowest AICc and RMSE which indicate the best model goodness-of-fit (Pham 2019). BIC would make no impact on the selection despite its controversial result to AICc and RMSE, as the selection required fitted model not correct model (Arijit & Jayanta 2011).

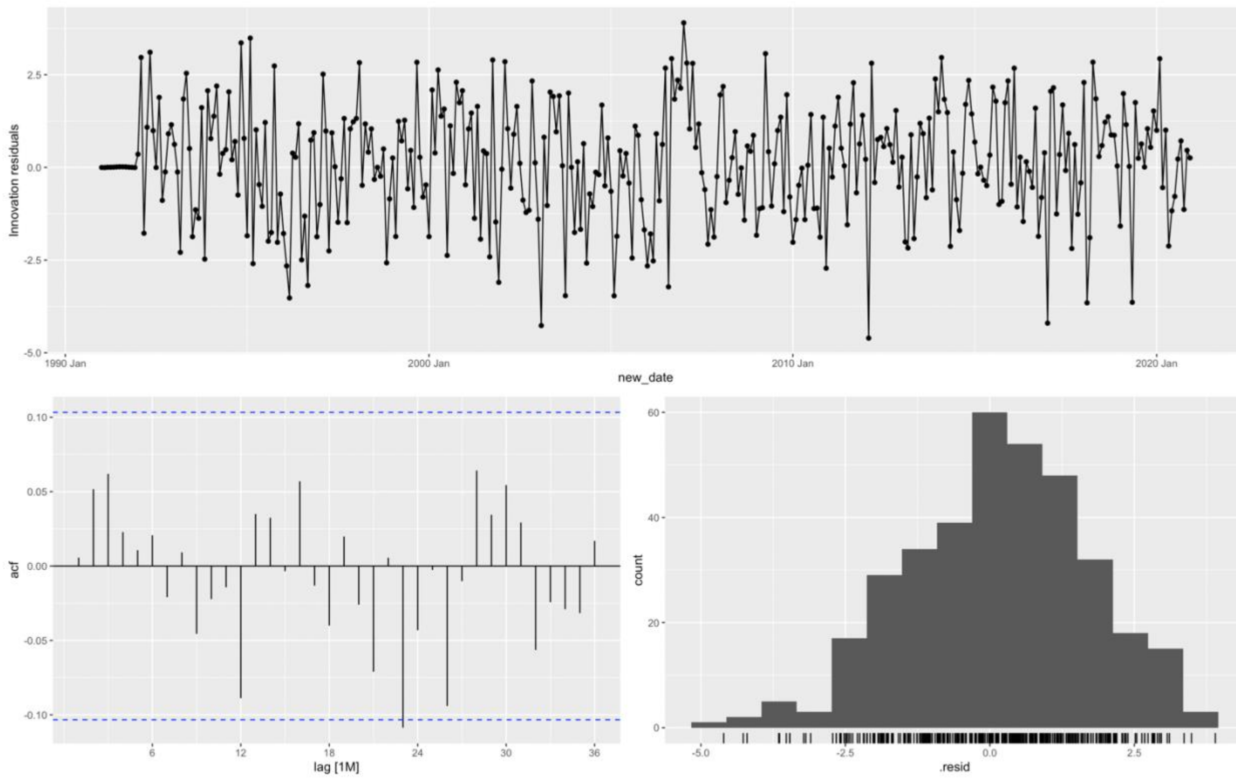


Figure 7. **Residual check for fitted ARIMA (3,0,3)(0,1,1)12**

Analyzing the residual would verify the absorption of data into selected model. As if the residuals are white noise or shows negligible, merely no autocorrelation, the model covers every necessary piece of information within the data (Box & Pierce 2012).

c. Diagnostic model

.model	lb_stat	lb_pvalue
arima303011	26.8	0.582

Table 3. **Ljung-box test result of fitted model.**

Ljung-box test depends on two entities, number of seasonal lags, here is monthly time series (lag = 36) and degree of freedom (dof = 7) retrieved from selected model. Like KPSS test, Portmanteau test also requires p-value to surpass 0,05 (5%) to clarify the residuals are white noise. Table 3 illustrates p-value of residuals from selected model at 0,582 (58,2%), hence passes the test.

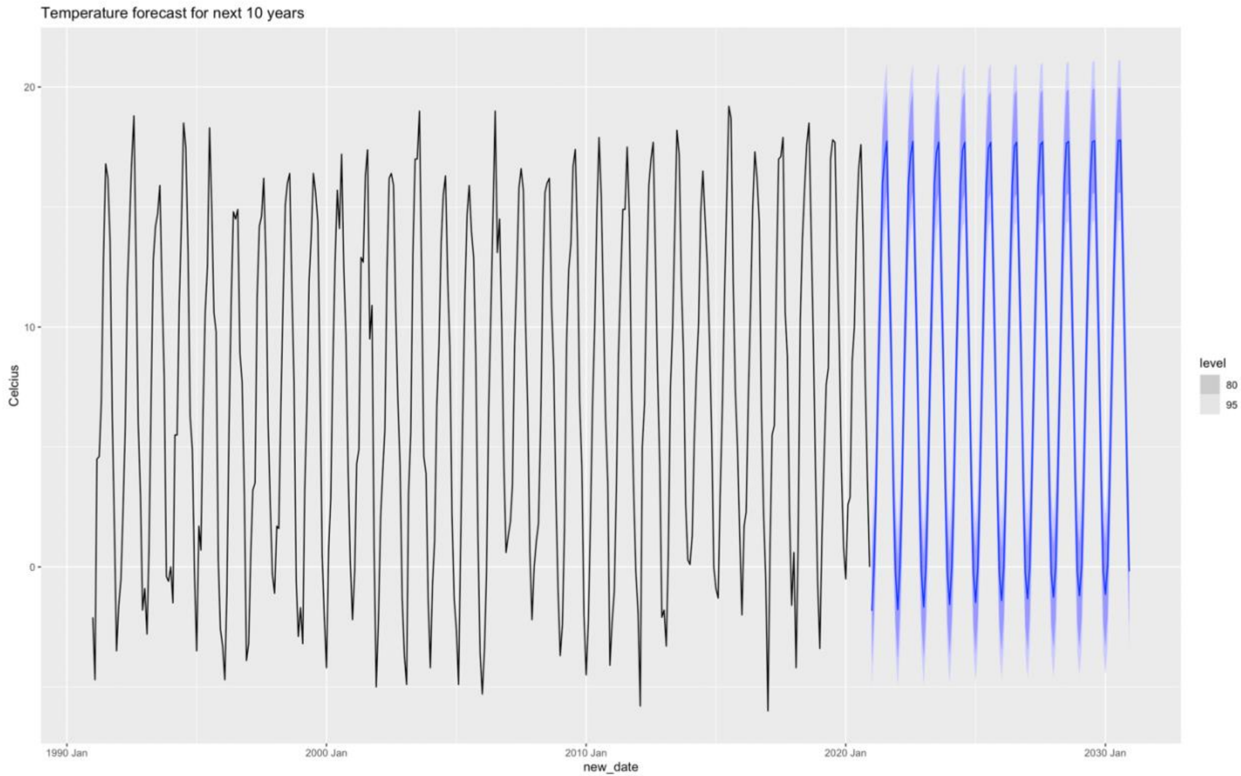


Figure 8. **10 year-forecast of Austria's Mean Temperature 2021-2031 (Unit: °C).**

Applying the chosen model, the 10-year-forecasting result provides corresponding outcome aligning with Austria's mean temperature time series described in Part 2a. The variance remains constant over time with unchanged proportional movement to the series. Hence, the model provides relatively grounded prediction.
Moreover, the seasonality pattern in projection is clear to witness which even supports the chosen SARIMA model to be the best fitted selection to forecast Austria's Mean Temperature in the next 10 years. However, the forecast fails to illustrate any peak or bottom level of degree compared to the real data in 1991-2020 dataset. Therefore, this forecast should be used or discussed on the surface value not to be widely applied and recognized as real-life value.

PART II – FORECASTING THE COMMODITY PRICES
(COMMODITY: Crude Oil)

a. About Crude Oil

Crude oil or petroleum, a more familiar form of crude oil, is one of the well-grounded fossil fuel founded million years ago after centuries of combining and pressing the dying algae, plant with other organic sentiments (Turgeon & Morse 2023). Nowadays, petroleum is stored in tremendous underground reservoirs and is extracted for commercial purposes by mechanical massive drills. The substance has diverse physical properties, especially specific gravity, the ratio divides the same amount of crude oil to water in standard climate (Britannica 2023). And API represents for gravity scale, crude oil would usually fluctuate around 15°-45° API and consists of two major valued crudes namely Brent and WTI; hence, crudes that have API exceed over the range would be categorized as extra-light or extra- heavy (Fitzgibbon n.d.). In terms of commodity market, crude oil is a core global trade goods under spot oil and even derivatives contracts. Its usage in propelling vehicles, heating buildings, etc. is vital and this substance remains primary energy sources for manufacturing despite renewable energy arise (Liberto 2023). Crude oil prices would be modified upon the volume of global trade, supply and demand. Economic development has a deep-rooted linkage with the fluctuation in oil price since when the economic expands demand for energy in manufacturing and daily consumption increases accordingly (eia 2022). Weather is also relevant to the supply of crude oil due because the refinery process and production would increase or decrease their resource distribution. Consequently, final market price is adjusted (eia 2022). Overall, as a vital commodity goods, oil price changes could provide some understanding about the current market level, including the purchasing power of household (Bokan et.al 2018; ECB 2004).

b. Time series plot recommended forecasting toolbox for price prediction

The dataset is majorly divided into 2 portions: training and test data. This methodology would estimate the parameters of determined forecasting approaches through training the data, then test data to result the forecasting accuracy (Gillis 2022). In this case, the training set starts from 1992 to 2021 and test set would lie in year 2022 to better examine the forecasting accuracy in later parts.

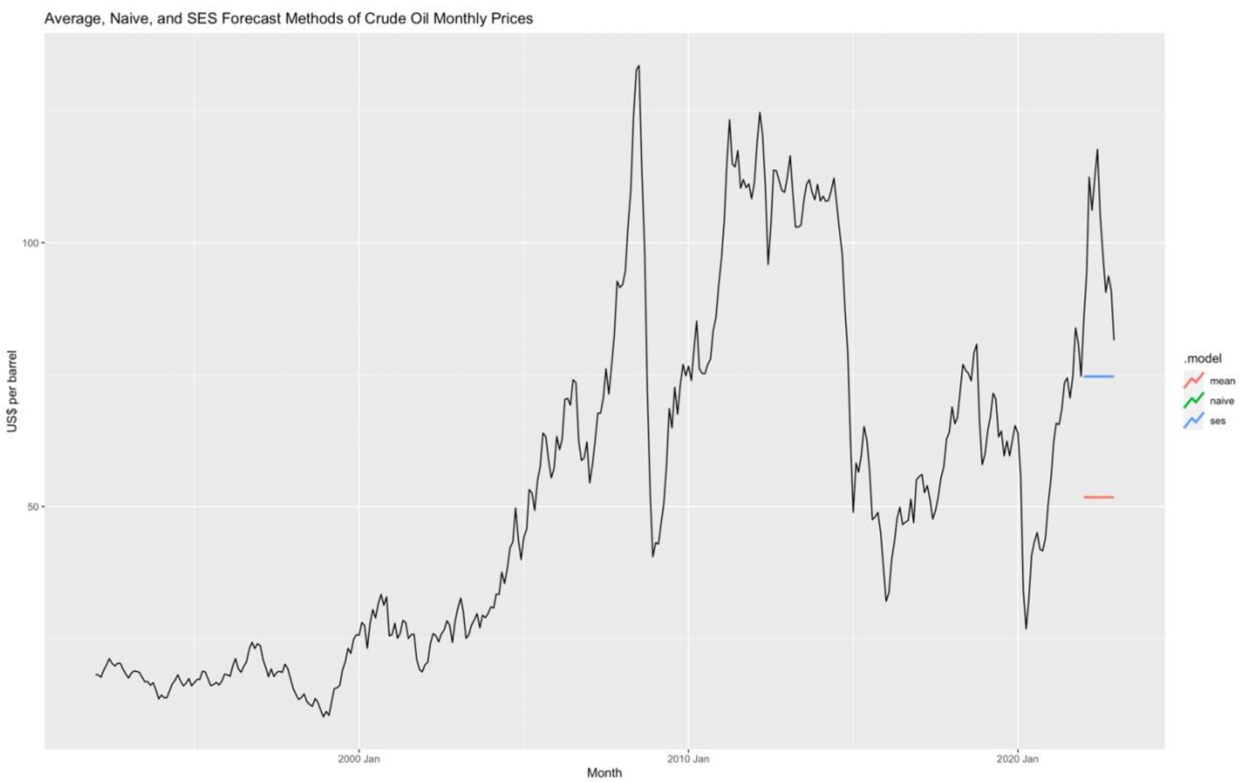


Figure 9. **Time plot of Average, Naïve and SES Forecast Methods of Crude Oil Monthly Prices 1992-2022 (Unit: US$ per barrel).**

On the one hand, Crude Oil price time plot displays a clear upward trend but obscured seasonality pattern, hence Naïve and Simple Exponential Smoothing (SES) would be preferred. As SES is likely to perform the prediction better than Average method when the time series data lacks seasonal patterns or autocorrelation with its past observations (Brownlee 2018). Above plot witnesses the missing line for Naïve method, this resonates for our method suggestion. Since the alpha of SES model is close to 1 ($\alpha = 0{,}9999 \approx 1$), then there would be more weighted to the last observation which is likely to be the description for Naïve practice. Henceforth, the two line is stacked over and illustrates only one line. This recommendation would be later verified through forecasting accuracy via checking residuals distribution and RMSE test.

c. Forecasting accuracy

Firstly, the training set fails to reach white-noised residuals in any practice (Appendix A). Hence, investigation on forecast errors examined the gap between observation and predicted values, this error is also defined as hidden and far-fetched predictable portion of the actual values.

Model	RMSE	MAE	MAPE
Mean	32.3	27.4	85.4
Naïve	4.84	3.26	6.77
SES	4.83	3.25	6.75

Table 4. **Forecasting accuracy measures of Mean, Naïve, SES methods**

SES method earns the lowest error to become the best fitted method compared to two remaining. As discussed, the accuracy in Naïve and SES is quite similar due to the alpha parameter in SES. To strengthen the selection, here is every month forecast and its actual value with self-calculated RMSE and MAE.

SES Method	Observation	Forecast	Error	Error^2	MAE	RMSE
1/1/2022	85.62	74.68	-10.9435	119.7601	**0,57**	**9.13**
2/1/2022	94.27	85.62	-8.6457	74.7484		
3/1/2022	112.44	94.27	-18.1739	330.2894		
4/1/2022	106.16	112.44	6.2825	39.4694		
5/1/2022	112.11	106.16	-5.9573	35.4893		
6/1/2022	117.69	112.11	-5.5797	31.1329		
7/1/2022	105.25	117.69	12.4393	154.7365		
8/1/2022	97.64	105.25	7.6111	57.9282		
9/1/2022	90.61	97.64	7.0356	49.5000		
10/1/2022	93.72	90.61	-3.1097	9.6701		
11/1/2022	90.94	93.72	2.7796	7.7263		
12/1/2022	81.50	90.94	9.4357	89.0331		

Mean Method	Observation	Forecast	Error	Error^2	MAE	RMSE
1/1/2022	85.62	95.96605	10.34	106.99	**3.03**	**11.46**
2/1/2022	94.27	95.96605	1.70	2.89		
3/1/2022	112.44	95.96605	-16.47	271.39		
4/1/2022	106.16	95.96605	-10.19	103.83		
5/1/2022	112.11	95.96605	-16.15	260.74		
6/1/2022	117.69	95.96605	-21.73	472.05		
7/1/2022	105.25	95.96605	-9.29	86.24		
8/1/2022	97.64	95.96605	-1.68	2.81		
9/1/2022	90.61	95.96605	5.36	28.71		
10/1/2022	93.72	95.96605	2.25	5.05		
11/1/2022	90.94	95.96605	5.03	25.27		
12/1/2022	81.50	95.96605	14.46	209.17		

Naïve method	Observation	Forecast	Error	Error^2	MAE	RMSE
1/1/2022	85.62	74.68	-10.94412008	119.7737644	**0,57**	**9.13**
2/1/2022	94.27	85.62	-8.644619048	74.7294385		
3/1/2022	112.44	94.27	-18.173	330.257929		
4/1/2022	106.16	112.44	6.284285714	39.4922469		
5/1/2022	112.11	106.16	-5.957922078	35.4968355		
6/1/2022	117.69	112.11	-5.579090909	31.1262554		
7/1/2022	105.25	117.69	12.43987013	154.750369		
8/1/2022	97.64	105.25	7.609813665	57.909264		
9/1/2022	90.61	97.64	7.03486166	49.4892786		
10/1/2022	93.72	90.61	-3.11038961	9.67452353		
11/1/2022	90.94	93.72	2.779935065	7.72803897		
12/1/2022	81.50	90.94	9.435454545	89.0278025		

Mean method seems to wrongly predict the oil prices, this might be caused by the random fluctuation from economic downturn. Hence, there is no big difference between choosing ETS or Naïve method. However, to earn every meticulous accuracy, we select SES.

d. Model illustration for 2024 monthly price forecast

The monthly price projection for crude oil in 2024 would perform the same price level as US$81.50413/ per barrel due to the alpha parameter of the chosen model (Figure 10;11).

ses	2024 Jan	*N(82, 330)*	81.50413
ses	2024 Feb	*N(82, 356)*	81.50413
ses	2024 Mar	*N(82, 381)*	81.50413
ses	2024 Apr	*N(82, 406)*	81.50413
ses	2024 May	*N(82, 432)*	81.50413
ses	2024 Jun	*N(82, 457)*	81.50413
ses	2024 Jul	*N(82, 483)*	81.50413
ses	2024 Aug	*N(82, 508)*	81.50413
ses	2024 Sep	*N(82, 533)*	81.50413
ses	2024 Oct	*N(82, 559)*	81.50413
ses	2024 Nov	*N(82, 584)*	81.50413
ses	2024 Dec	*N(82, 610)*	81.50413

Figure 10. **Monthly crude oil prices prediction for 2024 choosing ETS model (Unit: US$ per barrel).**

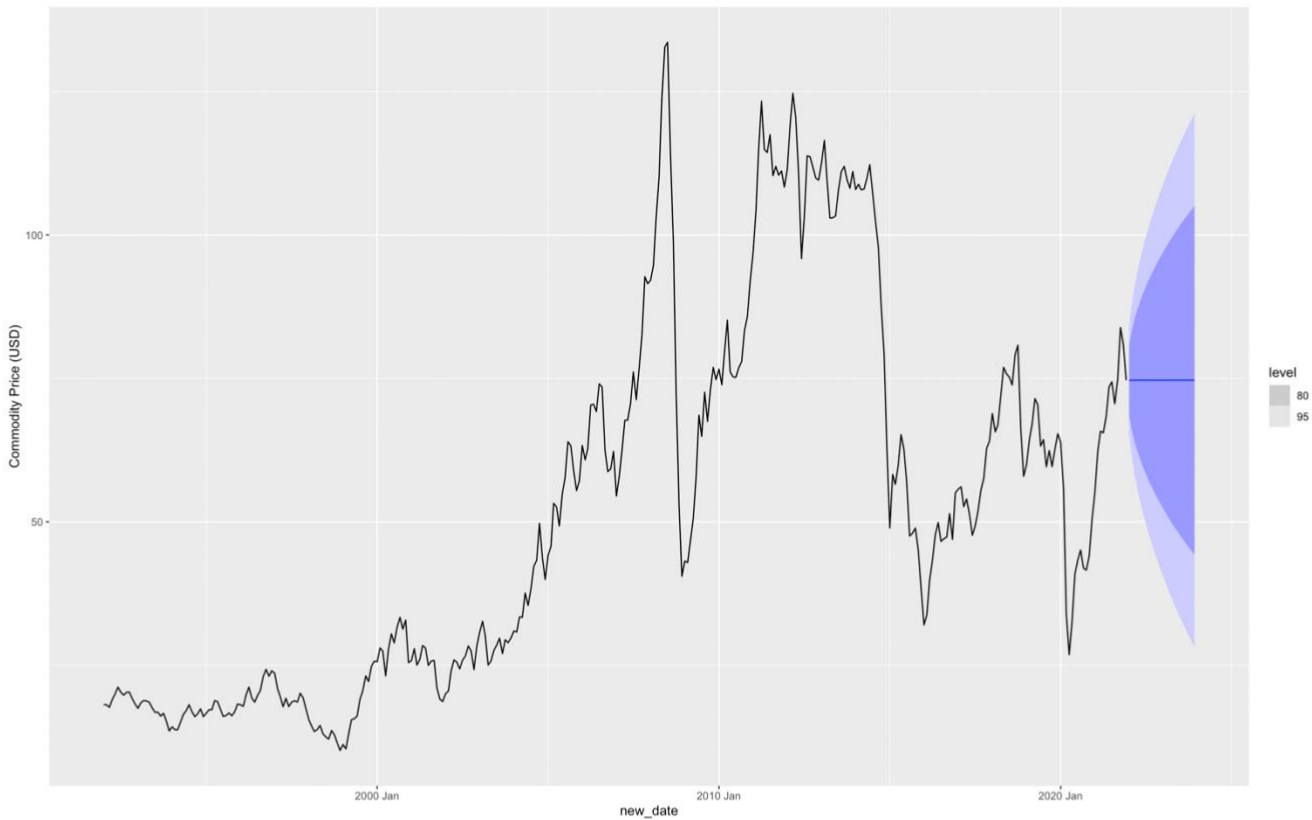


Figure 11. **Forecasting monthly crude oil prices in 2024. Unit: US$ per barrel.**

PART III – CONCLUSION AND DISCUSSION

a. Conclusion

In Part I, Austria's Mean Temperature data implies a moderately cool weather throughout the year since the average temperature fluctuates around 7,25°C. This is understandable despite diverse climatic zones of Austria since most of the territory is mountainous. The seasonality in Austria is detected clearly when people should wear warm in January and snow may start falling heavily from November. In non-technical manner, the forecast states that the temperature would maintain the seasonality and degree level throughout the next decade. However, in fact, this forecast would remain limited in actual usage because global warming and other environmental consequences are posing threats on majority of country on earth. Hence, the weather might fluctuate out-bounded from the prediction.

Part II is more economic-related when discussing about crude oil prices. Generally, the prices increase over time, especially when examine 1992-2022 period; the trend is clear. However, the forecast errors remain high which mean the actual prices should have been influenced by other factors, historical data fails to provide absolute accurate projections.

b. Policy recommendation

With the forecast, it is impossible to comment on the trend movement, upward or downward. Looking the plot, upward trend could be true to 1992-2022 period, however the seasonality or cyclical behavior is challenging to detect. Therefore, the fluctuation is unpredictable to forecast accurately. Based on the trend movement from part II, we recommend examining the policy thoroughly together with economic level, which sectors are dampened by rising oil prices to designate appropriate policy. Rising oil prices also hurt households, hence there should be policy to soothe the inflationary living cost, since when the prices keep rising, cost and final selling price accordingly increases.

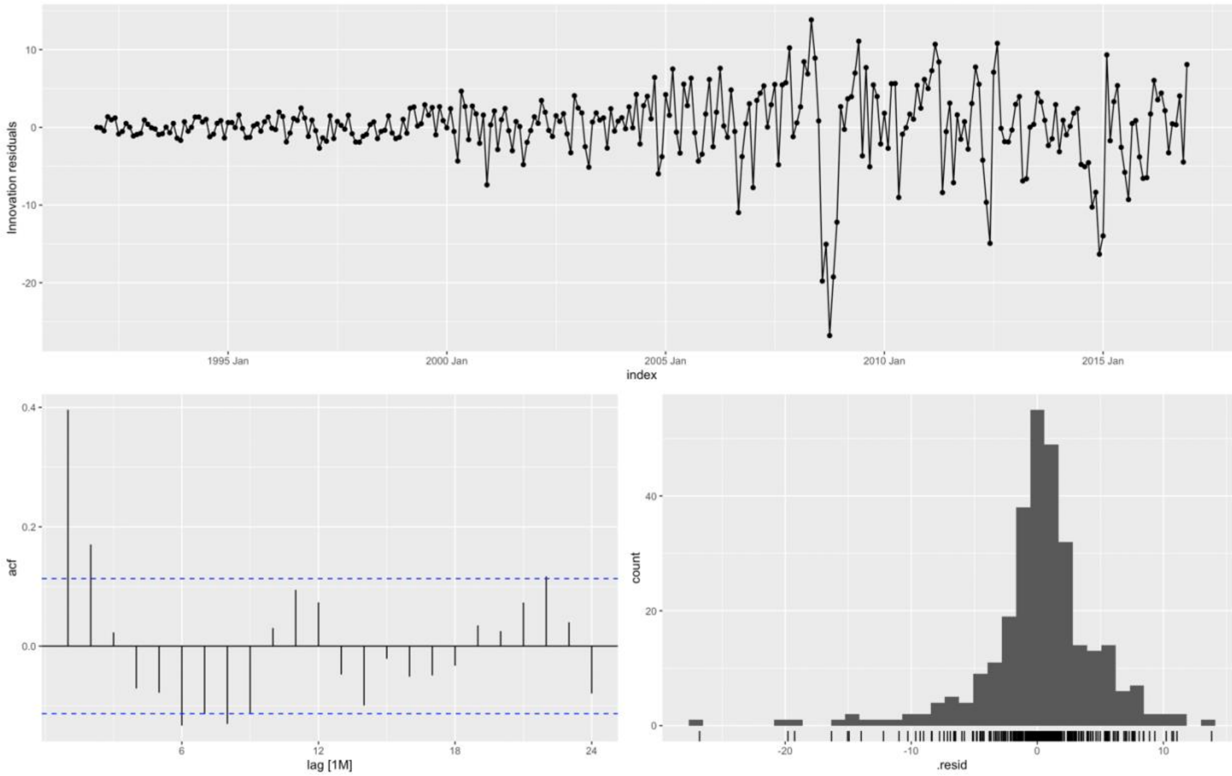
However, heavy reliance on the quantitative forecast would lead to biased policy suggestion. Therefore, it is believed to follow the volume of trade in the market to generate assumption on supply and demand level.

c. Limitation

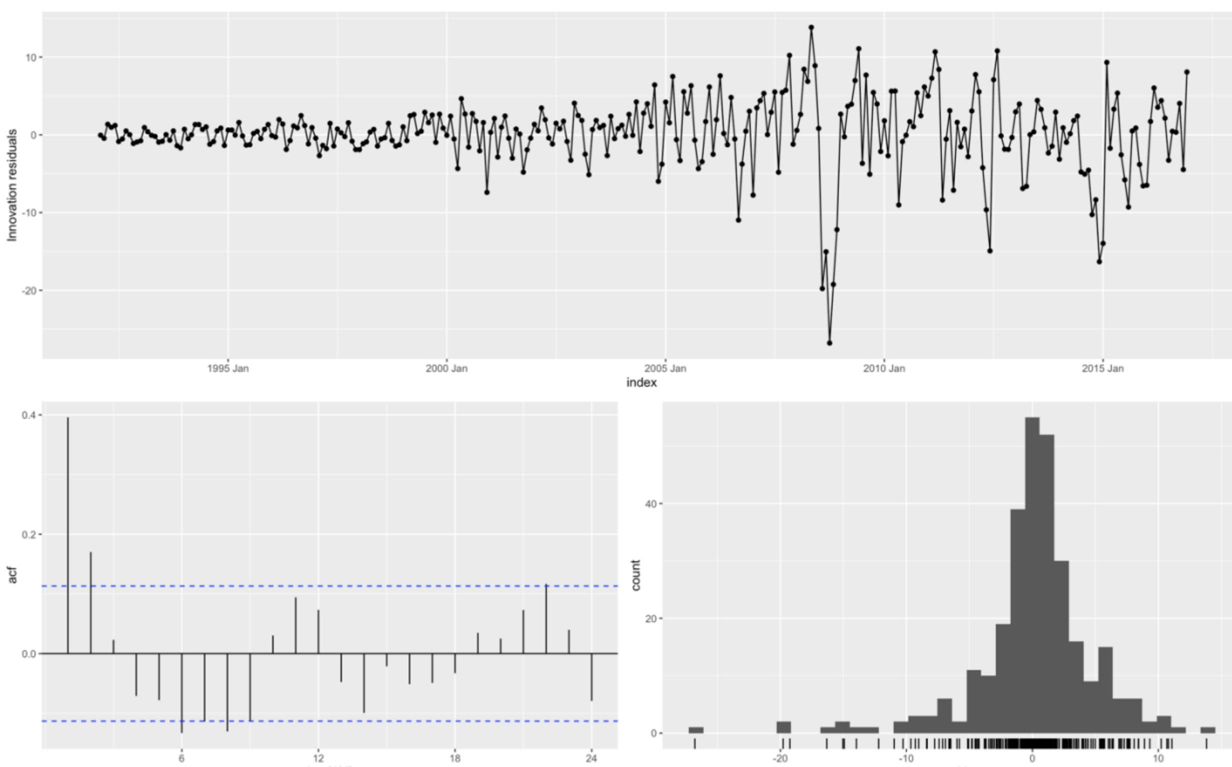
For part I, the data quantity is restricted from 1991-2020, hence this is not the latest updated data. Therefore, 2024 forecast might not earn the highest accuracy since actual temperature in 2021 and 2022 might be adjusted compared to our forecast. Moreover, the research mainly focuses on the temperature dataset itself without exploiting other information or causation within the data such as natural factors that can affect temperature such as geographical affects, monsoon, and climate humidity, etc. So, this outcome should be solely considered as surface value of the moderate temperature in Austria due to some forecast errors. In fact, Austria has such diverse climate zones, as explained assumption in part I, the dataset and forecast would be unable to reflect the entire Austria's mean temperature. Lastly, SARIMA model could exclusively state the linear relationship between temperature and time series data, hence this model would not efficiently exploit the utter relationship within the data (Zhang et.al 2013). Part II's limitation shares some similarities such as limited data quantity, lack of quantitative analysis. Applying forecasting accuracy to determine forecasting methods such as RMSE comparison could cause unreliability due to high dependence on data fraction (Maxim et. al 2013). Lastly, 3 proposed forecasting method still remains high errors, we could rely on this to prompt ultimate alternative method to gain lower error measures.

APPENDICES:

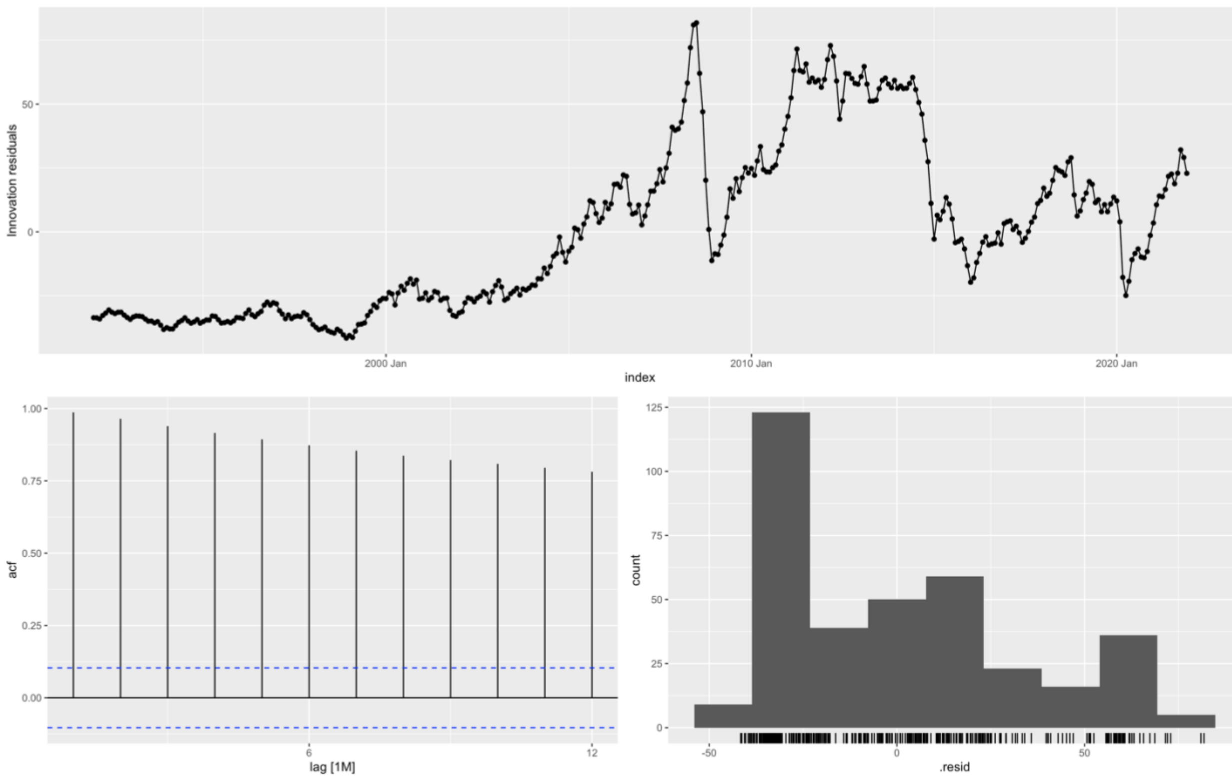
A- Residuals test for original dataset 1992-2022



A.1. SES method



A.2. Naïve method



A.3. Average method

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