Forecasting Price as a Function of Temperature in NYC

OPIM 5671 - Group 6

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Background:
Energy prices are an inevitable expense for businesses, especially those that operate in a typical business setting. Additionally, energy markets tend to be highly volatile due to many factors, like weather, inflation, the prices of other similar commodities, etc. Some businesses attempt to hedge these risks through energy contracts with their suppliers. While there are a variety of ways to address these risks, there are two common contract types. The first being an indexed contract where companies can pay less, or can even be paid by decreasing their energy consumption while the energy grid is under high demand. The second is a fixed rate contract where the energy supplier agrees to charge the same rate, (cost per kilowatt hour), for a fixed amount of time regardless of how energy markets change. Spot prices, when taken over time in a specific area, are a key indicator of changing energy rates and overall grid demand.

Business Problem:
For Stanwich Energy Advisors LLC, it would be extremely useful to have a tool that could be used to better advise clients on when the grid will likely be in high demand, when to best renew or enter into a fixed-rate contract, or what a profitable price for their contracts would be for a given year. The goal of this forecasting project was to devise a way to accurately forecast electricity spot prices in both the short and long term to advise existing clients how to manage their energy consumption if they are on an adjustable index contract and advising new/existing clients. Currently there is no forecast method in place, so any forecasting power would be seen as an improvement for Stanwich and other companies that provide similar services. It would also be extremely valuable to determine if temperature and the relationship it has with price could be used to forecast future prices, or if further information is necessary to make an accurate prediction.

Data Source:
Stanwich Energy Advisors LLC provided the data set for our exploration and model development; it is a combination of data purchased from OpenWeatherMap and NYISO.

Data Dictionary:

The Original Dataset
The data, upon receiving it from Stanwich, was spot prices collected hourly in New York City, in addition to some information on weather conditions and spans from 2010 to early 2022. Prior to pre-processing, the dataset had 20 columns and 505,811 rows. It was also fairly clean data with no missing values, however there were some extreme outliers present that indicated weather events or big changes in energy use, like the Covid-19 lockdown.

The original columns and their descriptions:
Interval: The time interval that the data was collected at DD/MM/YYYY hh:mm
Temp: The average temperature in degrees fahrenheit
Temp_min: The minimum temperature in degrees fahrenheit
Temp_max: The maximum temperature in degrees fahrenheit
Pressure: Atmospheric pressure

Humidity: Measured humidity
Feels_like: A derived temperature from pressure, humidity, wind_speed and temp.
Wind_speed: Measured speed of the wind.
Wind_deg: Wind directionality relating to a cardinal direction, with east being 0
Rain_1h: Amount of rain measured in the last hour
Rain_3h: Amount of rain measured in the last three hours
Snow_1h: Amount of snow measured in the last hour
Snow_3h: Amount of snow measured in the last three hours
Clouds_all: A variable defining cloud coverage
Weather_condition_id: A number that uniquely identifies the weather
weather_description: A qualitative description of the weather
Price: The spot price of electricity in New York State Zone J (New York City) in Megawatt Hours
Energy Loss: Amount of energy lost due to line losses
Congestion: Measure of energy lost due to localized demand

The Final Dataset:
The final dataset used for model development included 8 columns with 4,410 rows. The processing techniques will be explained in the next section of the report.

The final columns and their descriptions:
Date1: The aggregation of hourly data from hours to days
Maxprice: The maximum price for the day
Minprice: The minimum price for the day
Avgprice: The average price for the day
Maxtemp: The maximum temperature for the day
Mintemp: The minimum temperature for the day
Avgtemp: The average temperature for the day
Weather dummy: a dummy variable with a value of either 0 or 1 to indicate events that led to extreme energy prices

Variable Removal:
The first pre-processing step was to determine possible target variables and explanatory variables, while eliminating those that would not aid in our model development. Specifically, the team viewed price as a function of temperature and really wanted to explore this relationship, therefore we initially began with just the variables temp, price, and interval.

Max_temp and min_temp were removed because they did not seem to represent the temperature in the general area.

Wind_speed,Wind_deg, Rain_1h, Rain_3h, Snow_1h, Snow_3h, Clouds_all, Weather_condition_id, Weather_description, Pressure, Humidity, and Feels_like were removed because they are not likely to impact all areas of the city in the same fashion. Additionally, based on advice from domain experts, temperature will drive prices more than weather conditions because the variability of energy consumption comes from inside structures thus eliminating the effect of elements like snow or rain. For example, people will increase their energy consumption, by turning on their heat, in the winter regardless of whether it snows or not.

Energy loss and congestion were removed because they do not affect spot price, energy lost due to line losses (energy loss) and congestion are still billed to the energy consumer. It is not factored into the unit price, but rather adds units.

<u>Data Transformation:</u>

The next step was transforming the interval variable of our dataset. This variable, being hourly, was very hard to process due to the large amount of rows. It was also very granular and hard to read in plots, therefore we transformed the data using SQL in multiple steps, so that the insights could be most useful. The code below is a representation of how the interval format was changed to the proper format expected in the SAS software.

```
-- create daydate column as DDMONYYYY--------------------------
-- This can help to solve problems in data aggregation step ----
-- FORMAT=date9. is the SAS date format for DDMONYYYY-----------

PROC SQL;
   CREATE TABLE STSM.PRICE_TEMP_ADD_DAYDATE AS
   SELECT t1.interval,
          t1.temp,
          t1.price,
          /* daydate */
            (DATEPART(t1.interval)) FORMAT=date9. AS daydate
      FROM STSM.PRICE_TEMP t1;
QUIT;
```

The next challenge was the sheer size of our data and its granularity, 505,811 rows had extended processing times and an hourly forecast would not be beneficial to the consultants or their clients due to the fact that businesses don't make decisions on an hourly basis. Both of these problems were resolved by aggregating our timeID to a day measure, which reduced the rows to a 24th of the original data. This conversion would allow the advisors to speak about daily, weekly or monthly changes in price. We also added columns that calculated the min, max and average temp, as well as price for each day. The SQL code used to achieve this aggregation is shown below.

```
-- create max, min, avg columns for price and temp -----------
-- You can create these and other types of derived columns by using standard SQL ----
-- FORMAT=BEST7. chooses a datatype with length 7. Change if required ----

PROC SQL;
   CREATE TABLE STSM.AVG_MIN_MAX_PER_DAYDATE AS
   SELECT t1.daydate,
          /* maxprice */
            (MAX(t1.price)) FORMAT=BEST7. AS maxprice,
          /* minprice */
            (MIN(t1.price)) FORMAT=BEST7. AS minprice,
          /* avgprice */
            (AVG(t1.price)) FORMAT=BEST7. AS avgprice,
          /* maxtemp */
            (MAX(t1.temp)) FORMAT=BEST6. AS maxtemp,
          /* mintemp */
            (MIN(t1.temp)) FORMAT=BEST6. AS mintemp,
          /* avgtemp */
            (AVG(t1.temp)) FORMAT=BEST6. AS avgtemp
      FROM STSM.PRICE_TEMP_ADD_DAYDATE t1
      GROUP BY t1.daydate;
QUIT;
```

The new mintemp and max temp variables are different from the original because it is the minimum and maximum of the averaged temperatures across New York City of those recorded each day, not an absolute max or min among all the hourly observations. Additionally, the avgtemp variable would be considered an average of the average temperatures. The price variable is a simple calculation of min max and average over the original price variable within the 24 hour period of each day.

Adding the Weather Dummy Variable

After exploring the data and noticing multiple extreme spikes due to events like the polar vortex in 2014, it became necessary to add a new variable called "weather dummy," which was created to account for the abnormally high prices seen in the winters of 2013-2014, 2017-2018, 2021-2022. The dummy variable carried a value of either 0 or 1. The dates that were included in the extreme time frame had a value of 1 and all others had a value of 0. will allow the model to view these as events and in turn prevent the model from overfitting.

Variable Exploration:

The aggregation done on temperature and price left three of each variable: maximum, minimum, and average. This complicated the goal of relating temperature to price because each aggregation could have different relationships with the others. For instance, maximum price could have been just as influenced by minimum temperature (instigating more demand for heat) as it could by maximum temperature (instigating more demand for electrical climate control). Our approach to exploring the variables, then, was to test all of the binary combinations of price and temperature.

The initial hypothesis was that price and ambient temperature would be related, so just as temperature has strong seasonality, we expected price to exhibit similar patterns. However, we did not find this to be the case, even within specific years. We were also interested in whether there would be an overall positive trend to energy prices, reflecting rising costs in fuel. We did not see these trends either, as energy prices remained stationary over the time period in question.

We eventually concluded, when thinking about what the clients at Stanwich were asking for, that the models that predicted maximum and minimum price were not as useful for addressing our business problem as those that predicted average price. The goal would be to give energy management customers a good sense of what prices would be typically, and average price would be the best method of relaying that information in the clearest manner. Customers would be less interested in the cheapest or most expensive possible prices, but rather the price that they would be more likely to see. We kept the models that predicted those variables for comparison's sake, but we committed to selecting an average price model as our final model regardless of better fit or accuracy statistics, because ultimately the model is built to give insight to the business and aid in the effort to solve their problems.

Model methodology:

All three target variables (minprice, maxprice, avgprice) were tested using the Augmented Dickey-Fuller Unit Root Test to determine if the model were stationary. None of the variables showed significant seasonal pattern or trend; they also passed the unit root test indicating that the ARIMA model would be the best methodology to use, especially with the inclusion of two independent variables. We then decided to create nine total models, each with a target variable paired with an explanatory variable. The explanatory variables were also time series meaning these variables had to be prewhitened to reduce cross-correlations and determine the lag value that needed to be added to the SAS code to capture the most variation, which would lead to an effective use of the ARIMAX model.

The results of the Augmented Dickey-Fuller Unit Root Test were as follows (looking specifically at the single mean section):

1. **maxprice**

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-1542.90	0.0001	-30.56	<.0001		
	1	-952.573	0.0001	-21.80	<.0001		
	2	-664.625	0.0001	-17.55	<.0001		
Single Mean	0	-2626.82	0.0001	-43.22	<.0001	934.20	0.0010
	1	-2137.89	0.0001	-32.66	<.0001	533.19	0.0010
	2	-1838.11	0.0001	-27.53	<.0001	379.06	0.0010
Trend	0	-2707.76	0.0001	-44.16	<.0001	974.92	0.0010
	1	-2257.18	0.0001	-33.53	<.0001	562.06	0.0010
	2	-1986.57	0.0001	-28.39	<.0001	402.93	0.0010

2. **minprice**

Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-1120.24	0.0001	-25.21	<.0001		
	1	-706.043	0.0001	-18.63	<.0001		
	2	-433.924	0.0001	-14.17	<.0001		
Single Mean	0	-1971.54	0.0001	-35.48	<.0001	629.50	0.0010
	1	-1521.84	0.0001	-27.40	<.0001	375.29	0.0010
	2	-1061.91	0.0001	-21.50	<.0001	231.18	0.0010
Trend	0	-1973.50	0.0001	-35.50	<.0001	630.05	0.0010
	1	-1524.17	0.0001	-27.41	<.0001	375.68	0.0010
	2	-1063.76	0.0001	-21.51	<.0001	231.37	0.0010

3. **avgprice**

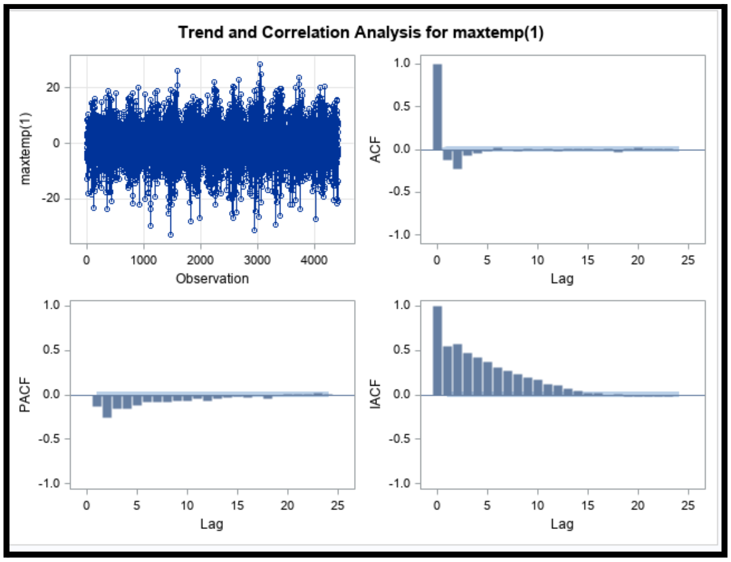
Augmented Dickey-Fuller Unit Root Tests							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-336.965	0.0001	-13.10	<.0001		
	1	-280.177	0.0001	-11.69	<.0001		
	2	-190.416	0.0001	-9.48	<.0001		
Single Mean	0	-905.244	0.0001	-22.29	<.0001	248.34	0.0010
	1	-861.311	0.0001	-20.54	<.0001	211.00	0.0010
	2	-647.249	0.0001	-17.11	<.0001	146.40	0.0010
Trend	0	-944.093	0.0001	-22.78	<.0001	259.56	0.0010
	1	-907.197	0.0001	-21.04	<.0001	221.34	0.0010
	2	-686.316	0.0001	-17.52	<.0001	153.61	0.0010

All three variables passed the unit root test, indicating that the price time series are stationary.

The results of the prewhitening phase were as follows:

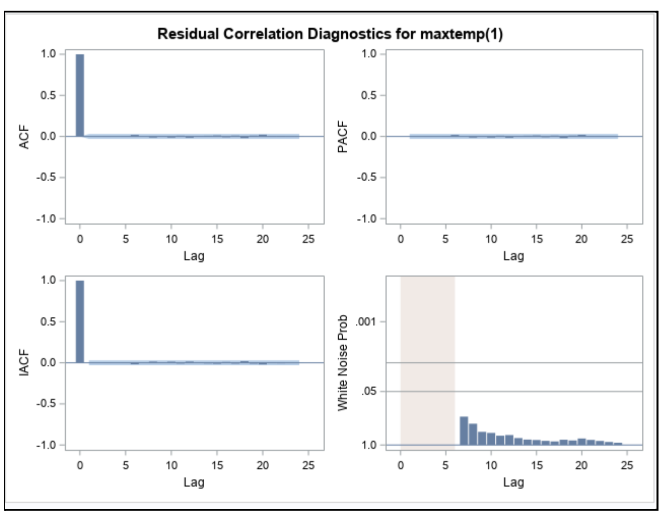
1. **maxtemp**

Exploring the first difference of max temp:



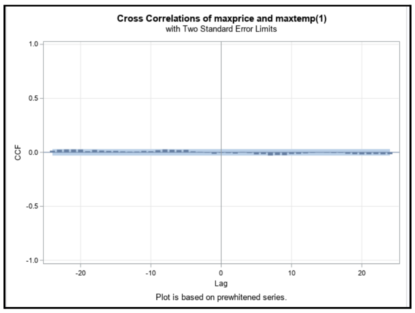
There is a clear need for a moving average model with 4 significant lags in the ACF chart. However, upon exploring there was also the need for an autoregressive component. An ARIMA(2, 1, 4) model resulted in white noise.

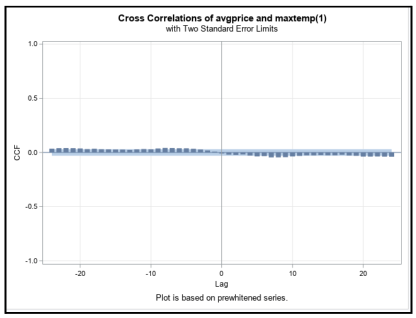
```
proc arima data=Work.preProcessedData plots
    (only)=(series(corr crosscorr) residual(corr normal)
        forecast(forecastonly));
    identify var=maxtemp(1);
    estimate p=(1 2) q=(1 2 3 4) method=ML;
    forecast lead=12 back=0 alpha=0.05 id=date1 interval=day;
    outlier;
    run;
quit;
```

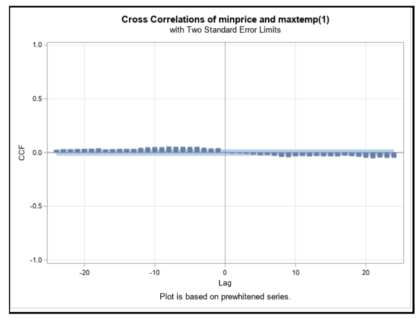


```
proc arima data=Work.preProcessedData plots
    (only)=(series(corr crosscorr) residual(corr normal)
        forecast(forecastonly));
    identify var=maxtemp(1);
    estimate p=(1 2) q=(1 2 3) method=ML;
    identify var=avgprice;
    estimate method=ML;
    forecast lead=12 back=0 alpha=0.05 id=date1 interval=day;
    outlier;
    run;
quit;
```

Changing the "identify var" to maxtemp allows us to explore which lagged effect of maxtemp needs to be used for our ARIMAX model constructions. Below the final cross-correlations can be seen for maxtemp with each explanatory price variable.

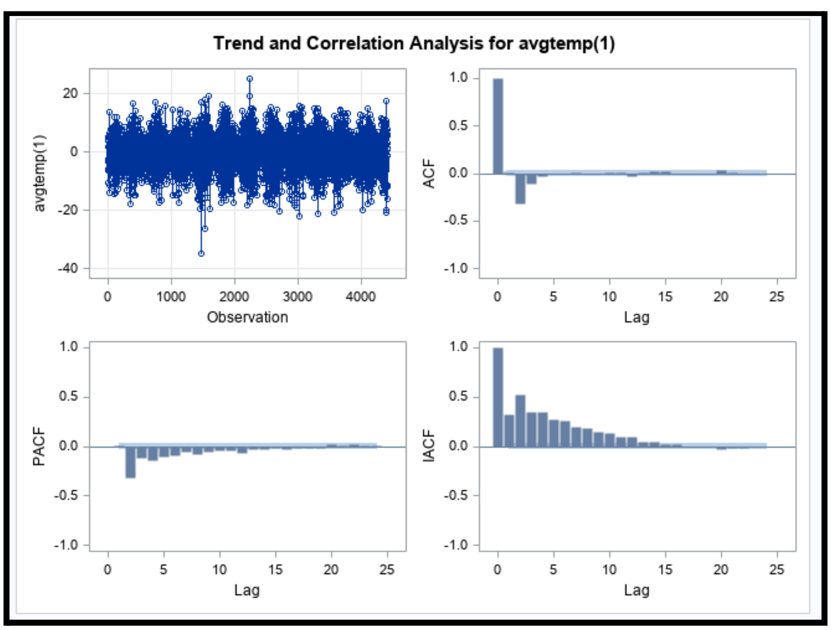






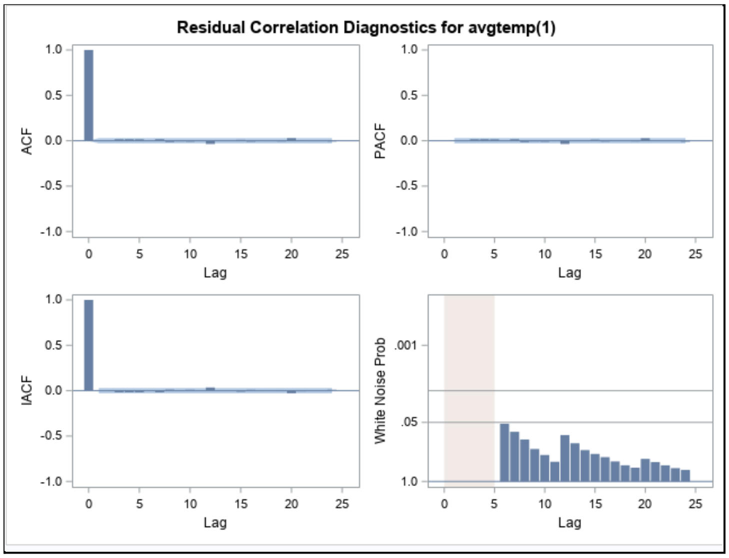
2. **avgtemp**

Exploring the first difference of avg temp we also saw the need for a moving average component of the ARIMA model:



In this case, a ARIMA(2,1,3) model resulted in whitenosie residuals:

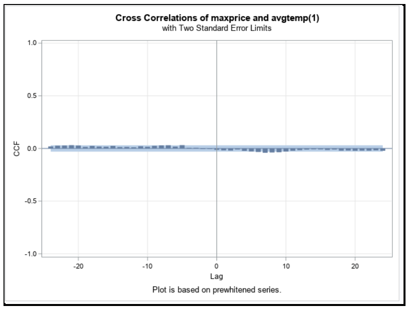
```
proc arima data=Work.preProcessedData plots
    (only)=(series(corr crosscorr) residual(corr normal)
        forecast(forecastonly));
    identify var=avgtemp(1);
    estimate p=(1 2) q=(1 2 3) method=ML;
    forecast lead=12 back=0 alpha=0.05 id=date1 interval=day;
    outlier;
    run;
quit;
```

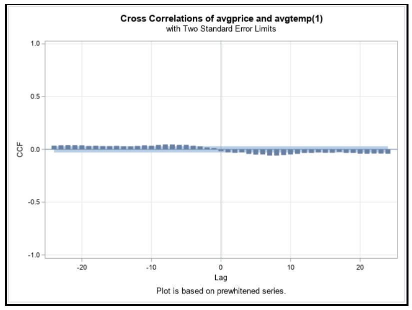


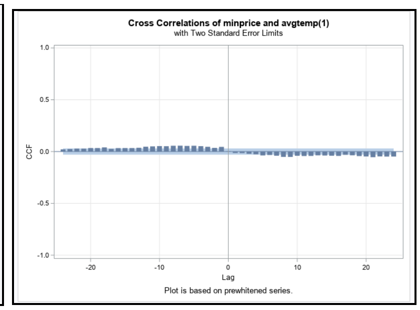
This exact model was applied to all three price variables to identify the significant avgtemp lags to include in the ARIMAX model building process:

```
22 proc arima data=Work.preProcessedData plots
23     (only)=(series(corr crosscorr) residual(corr normal)
24         forecast(forecastonly));
25     identify var=avgtemp(1);
26     estimate p=(1 2) q=(1 2 3) method=ML;
27     identify var=avgprice;
28     estimate method=ML;
29     forecast lead=12 back=0 alpha=0.05 id=date1 interval=day;
30     outlier;
31     run;
32 quit;
33
```

Once again, identify var was changed to reflect all the price variables (line 27) and their significant cross correlations were examined:

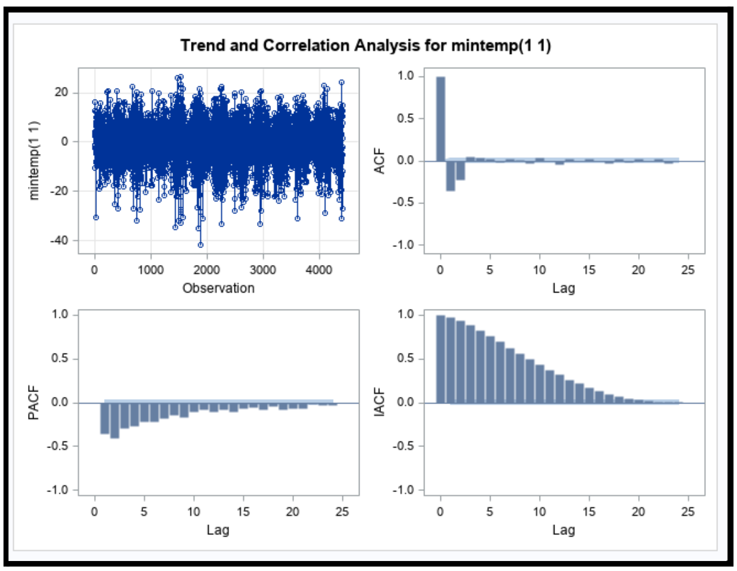






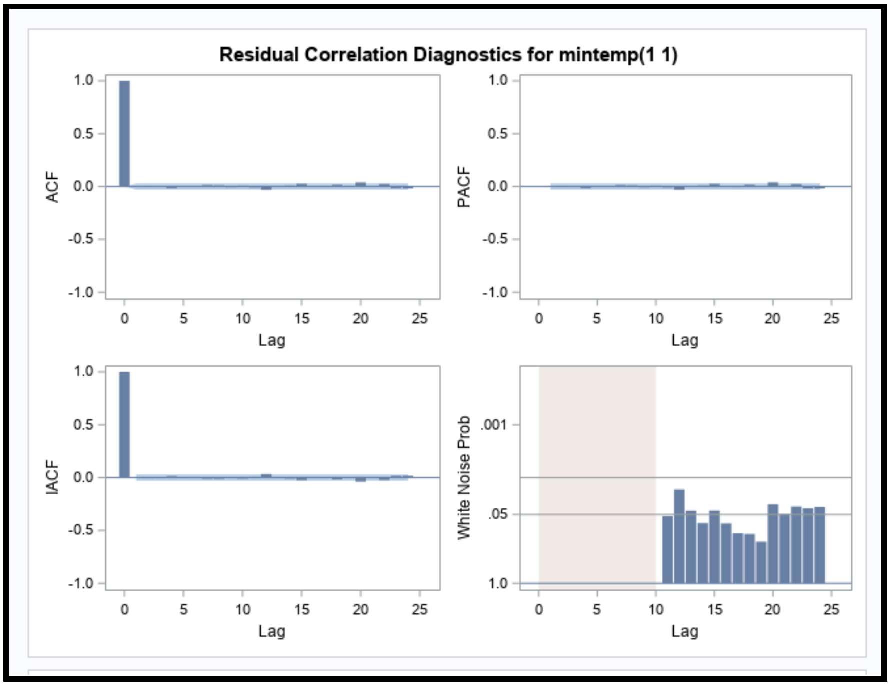
3. mintemp

The same process was followed for the mintemp variable, however we needed to take the second difference of mintemp inorder to build a model resulting in white noise:



Mintemp also required a much more complicated model in order to achieve white noise residuals:

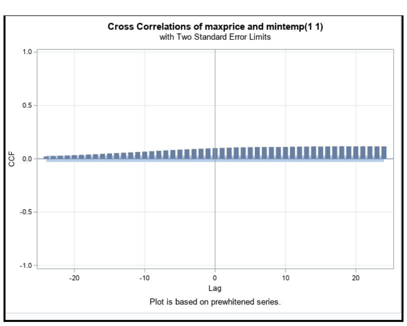
```
proc sort data=STSM.IMPORTWDUMMIES out=Work.preProcessedData;
    by date1;
run;

proc arima data=Work.preProcessedData plots
    (only)=(series(corr crosscorr) residual(corr normal)
        forecast(forecastonly));
    identify var=mintemp(1 1);
    estimate p=(1 2 3) q=(1 2 3 4 5 6 7) method=ML;
    forecast lead=12 back=0 alpha=0.05 id=date1 interval=day;
    outlier;
    run;
quit;
```

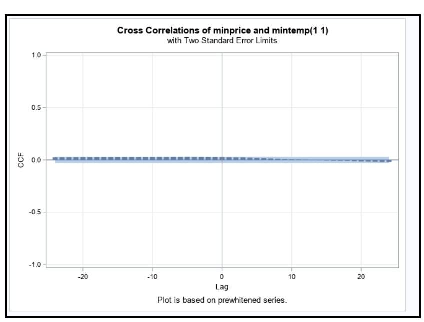


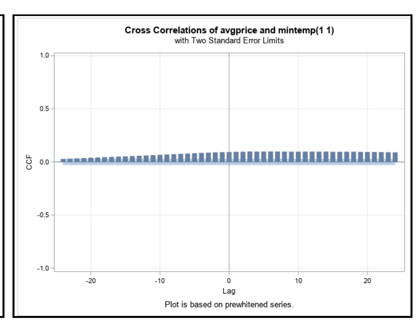
This exact model was then applied to all three price variables to see what significant lags there are when building the model, once again line 27, identify var, was changed to reflect all price variables:

```
22 proc arima data=Work.preProcessedData plots
23     (only)=(series(corr crosscorr) residual(corr normal)
24         forecast(forecastonly));
25     identify var=mintemp(1 1);
26     estimate p=(1 2 3) q=(1 2 3 4 5 6 7) method=ML;
27     identify var=avgprice;
28     estimate method=ML;
29     forecast lead=12 back=0 alpha=0.05 id=date1 interval=day;
30     outlier;
31     run;
32 quit;
```

The resulting cross correlation plots were as follows:







<u>ARIMAX Models:</u>

Although we did build all 9 models, as discussed earlier, we decided that the 6 models using both maxprice and minprice would not be useful for solving our business problem and focused our analysis and development on the avgprice models. We used a holdout sample of 365 days (1 year) and forecasted 365 days (1 year). Each model was explored, in regards to the value of the lag in the input, as well as the p and q value. The goal was to capture as much as possible and be left with white noise in the residuals. We discovered quickly that temperature is not the only determinant of energy prices and that changing these values would not capture all of the variability in the data, however we felt that these models could still provide some insight. Below, we will provide the code for each model, the parameter estimates, the panel of residual correlation diagnostics, the overall forecast, and the forecast for the holdback year. We will then review the fit and accuracy statistics to aid in the determination of the best model.

avgprice and avgtemp

This model, based on the cross-correlation plot, was constructed with a lag value of 4 in the input because lag 4 is where the bar exceeds the 95% confidence interval and becomes significant. A value of 4 for p, 6 for q, and d of 0 (because our data was initially stationary) was found to be best in terms of white-noise residuals.

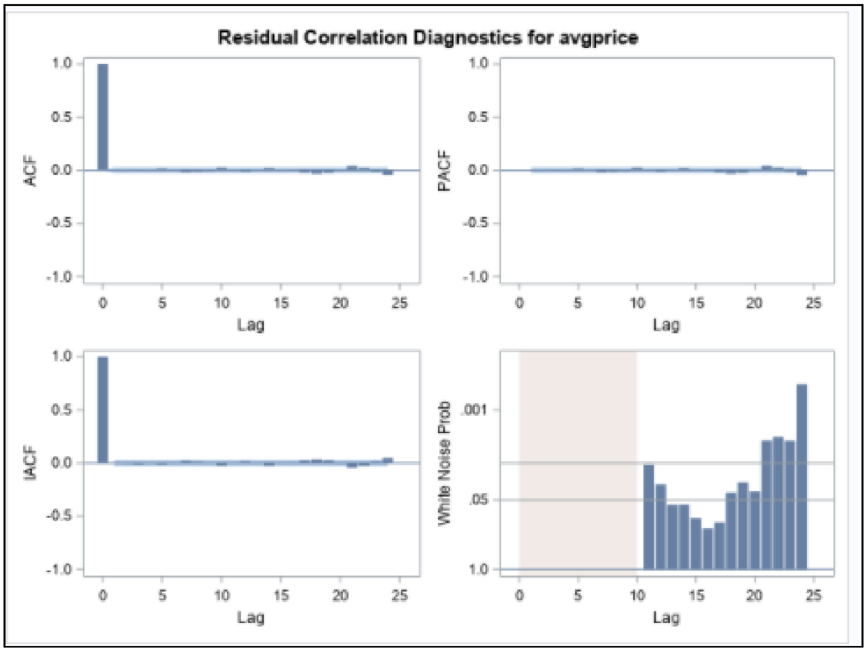
The code:

```
proc arima data=Work.preProcessedData plots
      (only)=(series(corr crosscorr) residual(corr normal)
         forecast(forecast forecastonly)) out=work.out0001;
    identify var=avgprice crosscorr=(avgtemp 'weather dummy'n);
    estimate p = 4 q = 6
    input=(4 $ avgtemp 'weather dummy'n) method=ML outest=work.outest0001
         outstat=work.outstat0001;
    forecast lead=365 back=365 alpha=0.05 id=date1 interval=day printall;
    outlier;
    run;
quit;

ods select all;

%accuracy(indsn=work.out0001, timeid=date1, series=avgprice,
    numholdback=&nhold);
run;
```

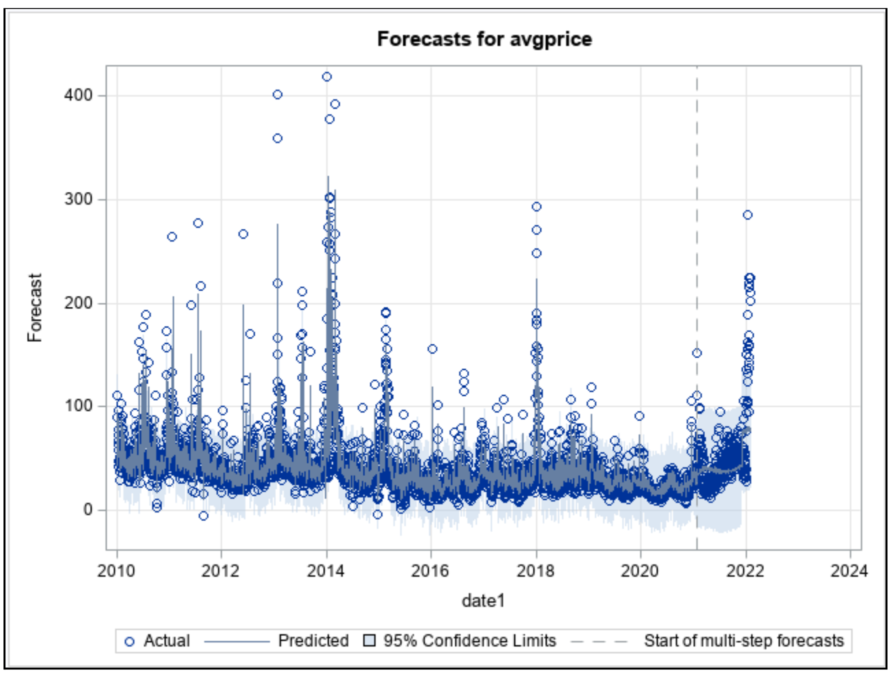
The Parameter Estimates:

Maximum Likelihood Estimation							
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	50.16741	3.98571	12.59	<.0001	0	avgprice	0
MA1,1	1.17350	0.20803	5.64	<.0001	1	avgprice	0
MA1,2	0.75550	0.42435	1.78	0.0750	2	avgprice	0
MA1,3	-1.13125	0.23178	-4.88	<.0001	3	avgprice	0
MA1,4	-0.09957	0.02860	-3.48	0.0005	4	avgprice	0
MA1,5	0.13509	0.02735	4.94	<.0001	5	avgprice	0
MA1,6	0.11642	0.03724	3.13	0.0018	6	avgprice	0
AR1,1	1.88845	0.20674	9.13	<.0001	1	avgprice	0
AR1,2	-0.16135	0.57105	-0.28	0.7775	2	avgprice	0
AR1,3	-1.56023	0.54968	-2.84	0.0045	3	avgprice	0
AR1,4	0.82777	0.18470	4.48	<.0001	4	avgprice	0
NUM1	-0.16449	0.05248	-3.13	0.0017	0	avgtemp	4
NUM2	32.96155	5.74357	5.74	<.0001	0	weather dummy	0

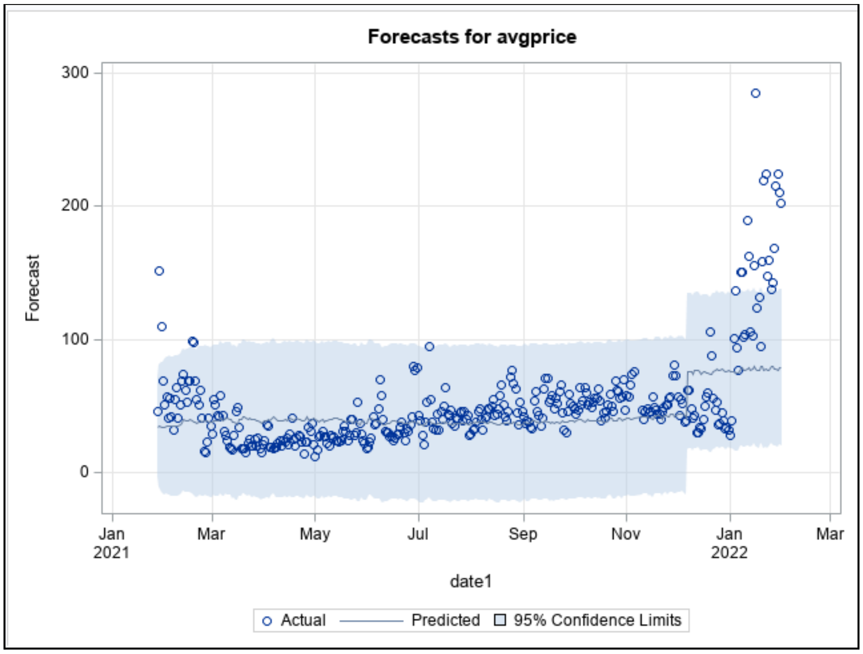
Panel of Residual Correlation Diagnostics:



The overall forecast:



The holdback period forecast:



As can be seen by these plots, the forecast, for the most part, seems to be within the confidence interval, however, January is definitely a problem period for this forecast. The step that can be seen in the forecast is a result of the weather dummy variable, but the variable still does not allow the capture of some of the higher values.

Model accuracy:

Series	Model	Holdback Periods	MAPE	MAE	MSE	RMSE
avgprice	work.out0001	4410	26.89%	10.7351	416.801	20.4157

avgprice and maxtemp:

This model, based on the cross-correlation plot was constructed with a lag value of 4 and 5 in the input because that is where the bar exceeds the 95% confidence interval and becomes significant. A value of 3 of p, 0 for d, and 5 for q was found to be the best in terms of white noise residuals.

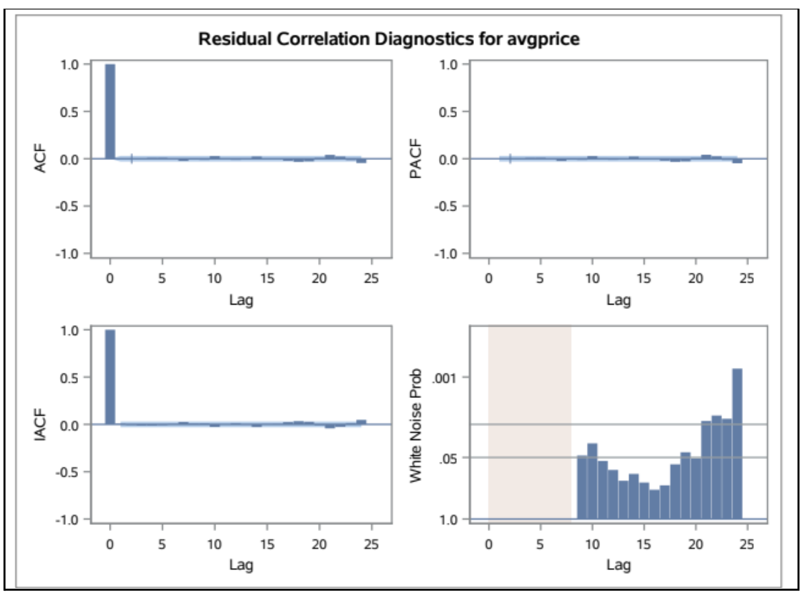
The code:

```
proc arima data=Work.preProcessedData plots
    (only)=(series(corr crosscorr) residual(corr normal)
    forecast(forecast forecastonly)) out=work.out0003;
    identify var= avgprice crosscorr=(maxtemp 'weather dummy'n);
    estimate p = 3 q = 5
    input=(4 $ maxtemp 5 $ maxtemp 'weather dummy'n) method=ML outest=work.outest0003
        outstat=work.outstat0003;
    forecast lead=365 back=365 alpha=0.05 id=date1 interval=day;
    run;
quit;
```

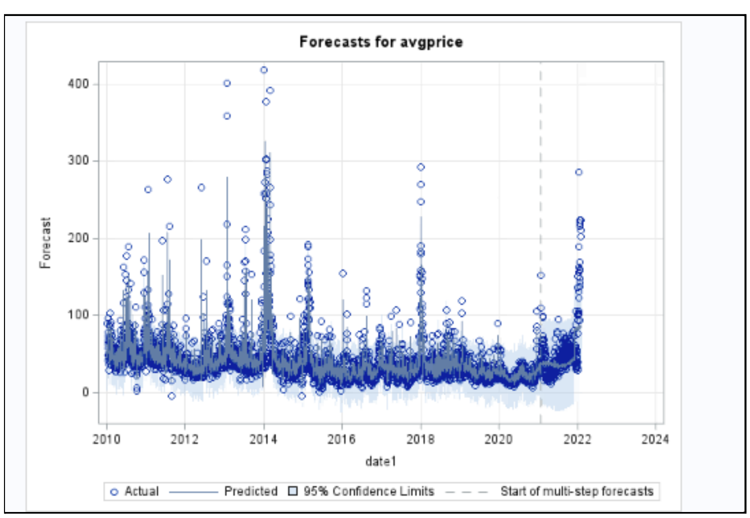
The Parameter Estimates:

Maximum Likelihood Estimation							
Parameter	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**	**Lag**	**Variable**	**Shift**
MU	54.05904	4.51661	11.97	<.0001	0	avgprice	0
MA1,1	2.08202	0.02319	89.77	<.0001	1	avgprice	0
MA1,2	-1.14068	0.04022	-28.36	<.0001	2	avgprice	0
MA1,3	-0.08956	0.03883	-2.31	0.0211	3	avgprice	0
MA1,4	-0.01232	0.03520	-0.35	0.7263	4	avgprice	0
MA1,5	0.13432	0.01719	7.81	<.0001	5	avgprice	0
AR1,1	2.79768	0.01691	165.48	<.0001	1	avgprice	0
AR1,2	-2.70831	0.03169	-85.47	<.0001	2	avgprice	0
AR1,3	0.90779	0.01549	58.62	<.0001	3	avgprice	0
NUM1	-0.12313	0.04213	-2.92	0.0035	0	maxtemp	4
NUM2	-0.08763	0.04211	-2.08	0.0374	0	maxtemp	5
NUM3	33.06061	5.71924	5.78	<.0001	0	weather dummy	0

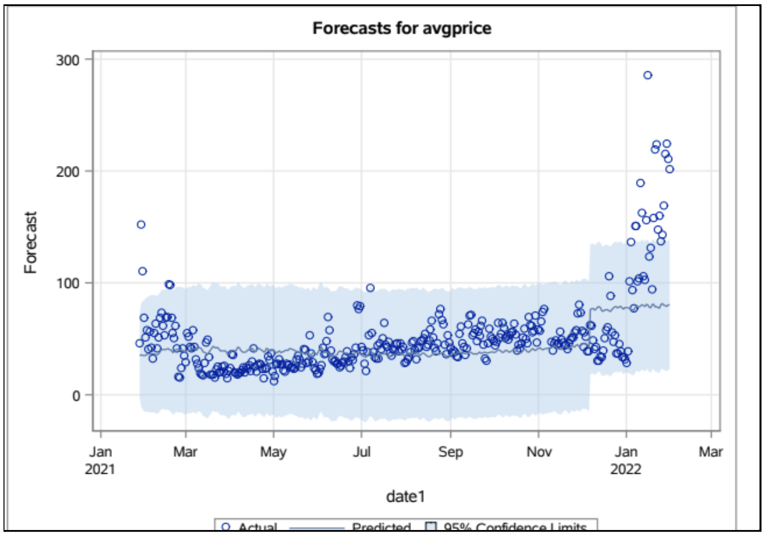
Panel of Residual Correlation Diagnostics:



The overall forecast:



The holdback period forecast:



As can be seen by these plots, the majority of the forecasts appear to be within the confidence interval. However, as with the other models, January is a problem period for this forecast. The inclusion of the weather dummy variable still did not allow the capture of some of the higher values.

Model accuracy:

Series	Model	Holdback Periods	MAPE	MAE	MSE	RMSE
avgprice	work.out0003	4410	26.87%	10.7183	415.197	20.3764

avgprice and mintemp:

This model, based on the cross-correlation plot, was constructed with a lag value of 1 and 2 in the input because that's where the bar exceeds the 95% confidence interval and becomes significant. A value of 4 for p and 6 for q was found to be best in terms of white-noise residuals.

The code:

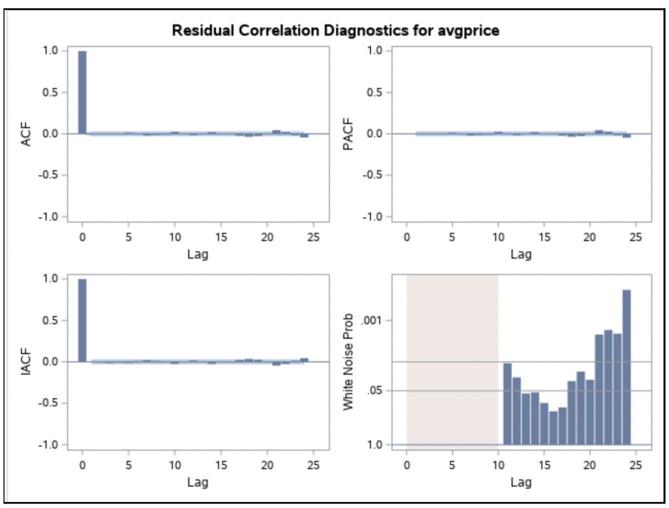
```
proc arima data=Work.preProcessedData plots
     (only)=(series(corr crosscorr) residual(corr normal)
        forecast(forecast forecastonly) ) out=work.mintempavgprice;
    identify var=avgprice crosscorr=('weather dummy'n mintemp);
    estimate p = 4 q = 6
    input=('weather dummy'n 1 $ mintemp 2 $ mintemp) method=ML
    outest=work.outest_new outstat=work.outstat_new;
    forecast lead=365 back=365 alpha=0.05 id=date1 interval=day printall;
    run;
quit;

ods select all;

%accuracy(indsn=mintempavgprice, timeid=date1, series=avgprice,
numholdback=&nhold);
run;
```

The Parameter Estimates:

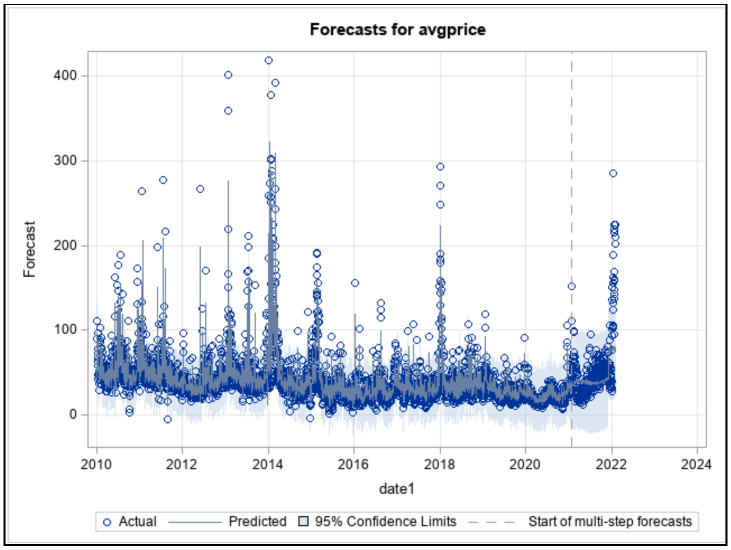
Correlations of Parameter Estimates

Variable Parameter	avgprice MU	avgprice MA1,1	avgprice MA1,2	avgprice MA1,3	avgprice MA1,4	avgprice MA1,5	avgprice MA1,6	avgprice AR1,1	avgprice AR1,2	avgprice AR1,3	avgprice AR1,4	weather dummy NUM1	mintemp NUM2	mintemp NUM3
avgprice MU	1.000	0.009	-0.004	-0.003	0.006	0.033	-0.010	0.005	-0.004	0.004	-0.003	-0.145	-0.494	-0.493
avgprice MA1,1	0.009	1.000	-0.994	0.964	0.361	0.489	-0.848	0.996	-0.994	0.987	-0.977	0.010	-0.014	-0.001
avgprice MA1,2	-0.004	-0.994	1.000	-0.985	-0.353	-0.461	0.852	-0.994	0.998	-0.997	0.992	-0.009	0.009	-0.001
avgprice MA1,3	-0.003	0.964	-0.985	1.000	0.261	0.389	-0.817	0.972	-0.983	0.990	-0.992	0.013	0.001	0.001
avgprice MA1,4	0.006	0.361	-0.353	0.261	1.000	0.044	-0.479	0.304	-0.308	0.312	-0.317	-0.022	-0.059	0.048
avgprice MA1,5	0.033	0.489	-0.461	0.389	0.044	1.000	-0.697	0.490	-0.488	0.482	-0.473	-0.007	-0.018	-0.032
avgprice MA1,6	-0.010	-0.848	0.852	-0.817	-0.479	-0.697	1.000	-0.842	0.850	-0.860	0.870	0.016	0.023	-0.002
avgprice AR1,1	0.005	0.996	-0.994	0.972	0.304	0.490	-0.842	1.000	-0.998	0.991	-0.981	0.008	-0.006	-0.004
avgprice AR1,2	-0.004	-0.994	0.998	-0.983	-0.308	-0.488	0.850	-0.998	1.000	-0.998	0.991	-0.009	0.005	0.003
avgprice AR1,3	0.004	0.987	-0.997	0.990	0.312	0.482	-0.860	0.991	-0.998	1.000	-0.998	0.011	-0.005	-0.003
avgprice AR1,4	-0.003	-0.977	0.992	-0.992	-0.317	-0.473	0.870	-0.981	0.991	-0.998	1.000	-0.014	0.006	0.003
weather dummy NUM1	-0.145	0.010	-0.009	0.013	-0.022	-0.007	0.016	0.008	-0.009	0.011	-0.014	1.000	0.065	0.061
mintemp NUM2	-0.494	-0.014	0.009	0.001	-0.059	-0.018	0.023	-0.006	0.005	-0.005	0.006	0.065	1.000	-0.217
mintemp NUM3	-0.493	-0.001	-0.001	0.001	0.048	-0.032	-0.002	-0.004	0.003	-0.003	0.003	0.061	-0.217	1.000

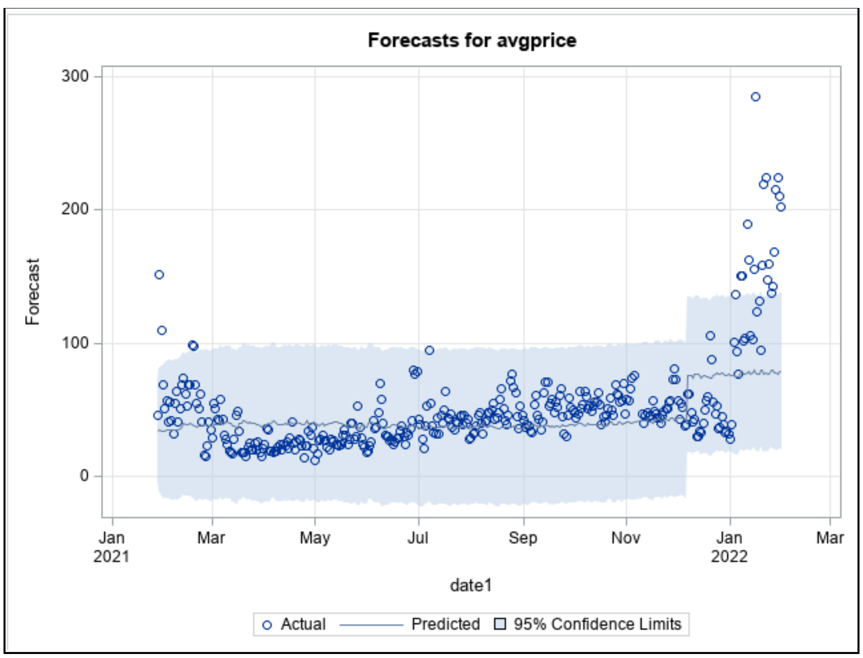
Panel of Residual Correlation Diagnostics:



The overall forecast:



The holdback period forecast:



Again, as visible in these plots, the forecast, for the most part, seems to be within the confidence interval, however, with January being a problematic period.

Model accuracy:

Series	Model	Holdback Periods	MAPE	MAE	MSE	RMSE
avgprice	mintempavgprice	4410	27.24%	10.7900	413.391	20.3320

Selecting the Best Model:

For all three models, the MAPE was very similar; the models all had between 25% and 27% mean absolute percentage error. Given this fact, we looked at the fit statistics, which took avg temp with max price out of the running due to the much higher values for AIC and SBC. With the last two models, it came down to usefulness for our business problem and we have chosen the model with avg temp and the weather dummy as the independent variables and the avg price as the dependent variable, as the best model. This model, intuitively, provides the most insight to Stanwich and other entities or individuals who may need this type of information. This model is a decent starting point, but could definitely be improved.

By looking at the white noise probabilities from the residuals, there is definitely some variability that is not being captured. This model could be improved by adding more independent variables or by having a more complex dummy variable. Due to the current lack of any model, this is a step in the right direction and with more work could be incredibly useful and accurate.

X	Y	MAPE	AIC	SBC
Mintemp	avgprice	25.31%	38449.77	38539.25
Avgtemp	avgprice	26.89%	38451.06	38534.14
Maxtemp	avgprice	27.24%	42810.22	42823.00

Effect on Business Problem:

Our model is an attempt to build a model for a relationship that has not been built before; currently Stanwich does not use a forecasting model to advise clients. Therefore, this model is a drastic improvement to current methodology. This model would have two major impacts on the energy market. First, for existing clients with indexed contracts, short-term average price forecasts would allow advisors to inform clients when best to reduce their energy consumption. Due to the conditions of their contracts this will cause drastic energy rate reductions as high energy spot prices are a result of high grid demand. The second application is for existing clients looking to renew their fixed rate contracts or new clients looking for the best time to start a contract inorder to hedge their consumption risks. A long-term forecast will allow advisors to identify when the most likely time would be to get a low fixed rate, this would prevent uncertainty when calculating budgets as the rate stays the same regardless of client usage or the energy market, however it would ruin customer relationships if they were locked in at a high fixed rate. Therefore this model will allow the advisors to identify when to enter their contracts, but also when not to sign a contract and to wait for a more certain time with a lower, more standard rate. There are more, but less common applications of this model as well. It can be used to estimate savings when consulting on green energy projects to lower client usage or renewable and energy storage initiatives.