Term paper ENE434: Texas Energy Crisis

Candidate number:

Abstract

This is an example abstract

The Texas Energy crisis was a series of rolling power blackouts that resulted in billions of dollars worth of loss, and estimated 151 lives lost. A record cold wave hit the majority of mainland United States resulting in sustained temperatures well below 0 degrees celsius. The contrast between the record temperatures induced by the coldwave and normal winter temperatures was particularly stark in the south of the United States. The majority of homes and businesses in Texas rely on heating by resistive heating or reversed-refrigeration. In particular, over 60 % of homes rely entirely on electrical power for heating. As many of the power generating facilities lacks winterization, all types of energy generation sources saw a reduction in a net generation. The combination of substantially increased demand and reduction in power generation lead to the decision of ERCOT to reduce load on the electrical grid. This was an unevitable outcome, as the ever strained power generation and increasing power demand will lead to a decrease in frequency unless load is shed. Such a frequency drop may damage equipment, and cause instability across the grid. In the United States power generation is synchronized to operate at 60 hz, with adverse affects occurring already at 0.6 hz decrease in frequency. The two largest energy sources, natural gas and wind power, went through the largest reductions in net output of all sources.

In this analysis I will look at.....

1. Data exploration

Unfortunately, the power generation data collected for this analysis only goes back to 2018 of july and as a result the table

```
# Minimum, 25%-percentile, Mean, Median, 75%-percentile and Maximum by month

# Create table data

table_power_input_data <- demand_data_daily %>% filter(date > "2018-07-01") %>%
  left_join(generation_daily %>% filter(type == "total"), by = c("date")) %>%
  filter(!is.na(mWh_generated))



tibble(Type = "Power demand",
```

Table 1: Summary statistics of power generaton and power demand in Texas (from 2018-07)

Type	Minimum	Max	Maximum date	Minimum date	25% - percentile	75% - pe
Power demand	32222.50	62018.08	2021-02-14	2018-10-21	37458.33	4
Power generation	32222.21	60828.08	2021-02-14	2018-10-21	37435.08	4

Table 2: Maximum difference in power demand and total power generation

Maximum deviation	Maximum deviation date
1752.708	2018-07-02

```
       Minimum = min(table_power_input_data$mWh_demand_daily),
       Max = max(table_power_input_data$mWh_demand_daily),
       "Maximum date" = table_power_input_data[which.max(table_power_input_data$mWh_dema
       "Minimum date" = table_power_input_data[which.min(table_power_input_data$mWh_dema
       "25% - percentile" = quantile(table_power_input_data$mWh_demand_daily, 0.25),
       "75% - percentile" = quantile(table_power_input_data$mWh_demand_daily, 0.75)) %>%
  bind_rows(
    tibble(Type = "Power generation",
       Minimum = min(table_power_input_data$mWh_generated),
       Max = max(table_power_input_data$mWh_generated),
       "Maximum date" = table_power_input_data[which.max(table_power_input_data$mWh_gene
       "Minimum date" = table_power_input_data[which.min(table_power_input_data$mWh_gene
       "25% - percentile" = quantile(table_power_input_data$mWh_generated, 0.25),
       "75% - percentile" = quantile(table_power_input_data$mWh_generated, 0.75)),) %>%
  kbl(caption = "Summary statistics of power generaton and power demand in Texas (from 2
    kable_classic(full_width = F, html_font = "Times new roman")
```

```
tibble("Maximum deviation" =max(table_power_input_data$mWh_demand_daily - table_power_in
       "Maximum deviation date" = table_power_input_data[which.max(max(table_power_input
                                                                         table_power_inp
    kbl(caption = "Maximum difference in power demand and total power generation") %>%
    kable_classic(full_width = F, html_font = "Times new roman")
```

The temperatures are below are averages taken from three weather stations dispersed around the state of Texas.

```
# Minimum, 25%-percentile, Mean, Median, 75%-percentile and Maximum by month

# Create table data

table_power_input_data <- demand_data_daily %>% filter(date > "2018-07-01") %>%
```

Table 3: Summary temperature statistics

Average temperature	Max average temperature	Max average temperature date	Minimum average te
19.27449	33.6	2011-08-02	

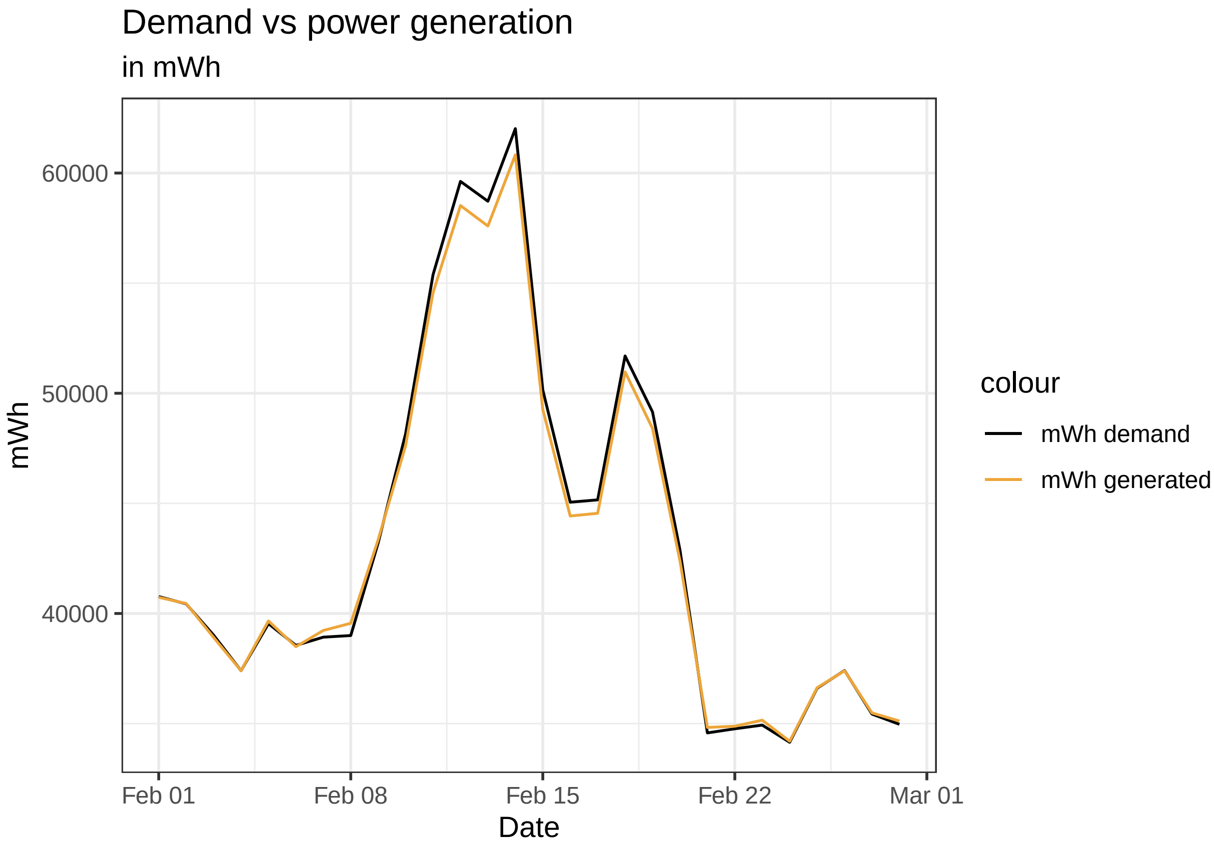
```
  left_join(generation_daily %>% filter(type == "total"), by = c("date")) %>%
  filter(!is.na(mWh_generated))
```

```
temperature_table_data <- texas_temperature %>% filter(!is.na(temp_max))
# Remove clear outliers
temperature_table_data %<>% filter(!temp_min < -40)


tibble("Average temperature" = mean(texas_temperature_avg$temp_avg),
       "Max average temperature" = max(texas_temperature_avg$temp_avg),
       "Max average temperature date" = texas_temperature_avg[which.max(texas_temperatur
       "Minimum average temperature" = min(texas_temperature_avg$temp_avg),
       "Minimum average temperature date" = texas_temperature_avg[which.min(texas_temper
       "Absolute maximum temperature" = max(temperature_table_data$temp_max),
       "Absolute maximum temperature date" = temperature_table_data[which.max(temperatur
       "Absolute minimum temperature"       = min(temperature_table_data$temp_min),
       "Absolute minimum temperature date" = temperature_table_data[which.min(temperatur
  kbl(caption = "Summary temperature statistics") %>%
    kable_classic(full_width = F, html_font = "Times new roman")
```

In the few periods in which the flow of power to customers were not interrrupted, the prices rose in tandem with the shortage of power generation. Cases of several thousand dollar electricity bills were not uncommon

Power generation and demand in february

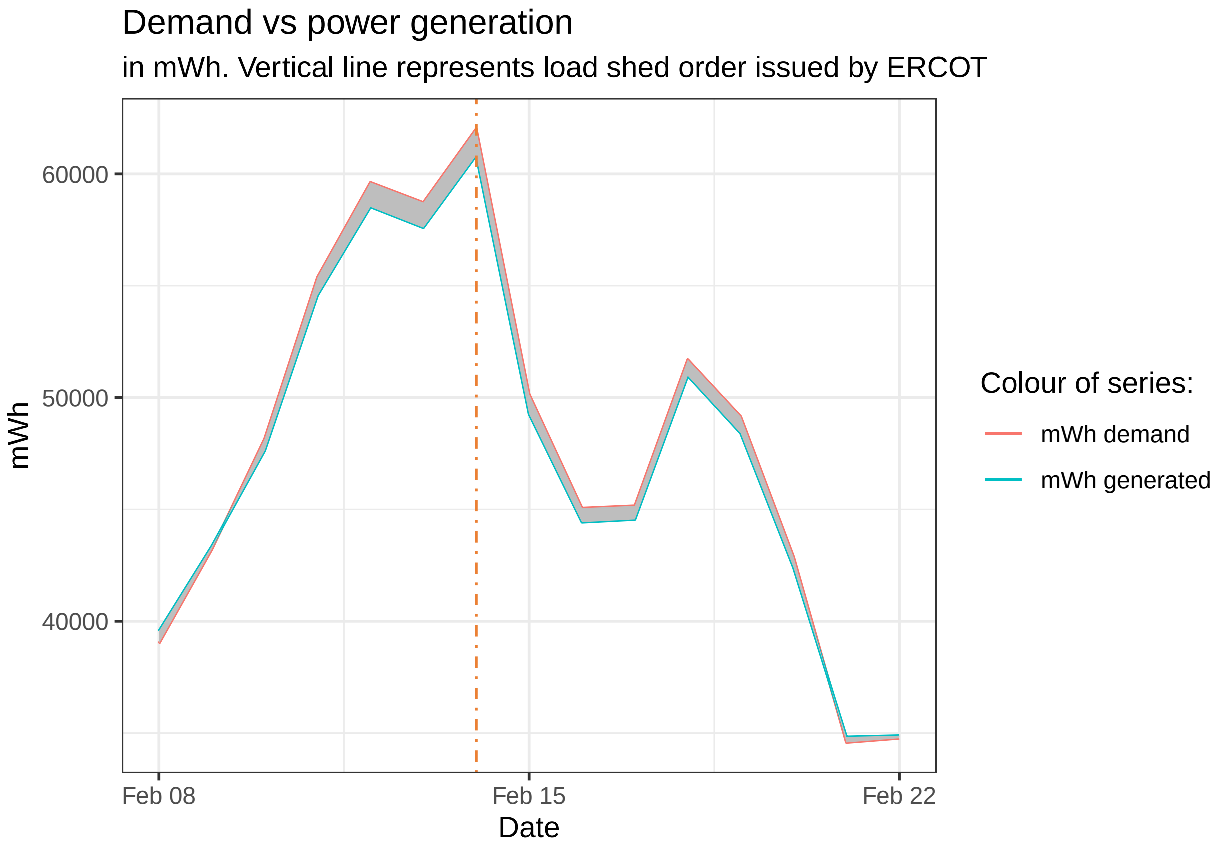
```
### Energy generation by source in february

demand_data_daily  %>%
  filter(month(date) == 2 &
           year(date) == 2021) %>%
  ggplot() +
  geom_line(aes(x = date, y = mWh_demand_daily, col = "mWh demand")) +
  geom_line(aes(x = date, mWh_generated, col = "mWh generated" ),
            data = generation_daily %>% filter(
              month(date) == 2 &
              year(date) == 2021 &
              type == "total"
            )) +
  scale_colour_manual(values = color_scheme) +
  labs(title = "Demand vs power generation", subtitle = "in mWh",
       x = "Date", y = "mWh") +
  theme_bw()
```



We can see that net generation exceeds in particular around February 14th, where ERCOT decided to shed load to preserve grid stability. We will explore those days closer in the next plot.

```
### Closer look at load sheds days

#load_sheds <- data.frame(date = lubridate::ymd(c("2021-02-14")),
 #                         load_shed = c())





demand_data_daily  %>%
  filter(date > "2021-02-07" &
         date < "2021-02-23") %>%
  mutate(mWh_generated = (generation_daily %>%
              filter(date > "2021-02-07" &
              date < "2021-02-23",
              type == "total"
            ))$mWh_generated) %>%
  ggplot() +
  geom_line(aes(x = date, y = mWh_demand_daily, col = "mWh demand")) +
  geom_line(aes(x = date, mWh_generated, col = "mWh generated" )) +
  geom_ribbon(aes(x = date, ymin = mWh_demand_daily,
                  ymax = mWh_generated), fill = "grey") +
 geom_vline(xintercept = as.numeric(as.Date("2021-02-14")),
            linetype = 4, col = "#eb8034") +
  scale_colour_manual(values = color_scheme) +
  labs(title = "Demand vs power generation", subtitle = "in mWh. Vertical line represent
       x = "Date", y = "mWh") +
  theme_bw() +
  scale_colour_discrete("Colour of series:")
```

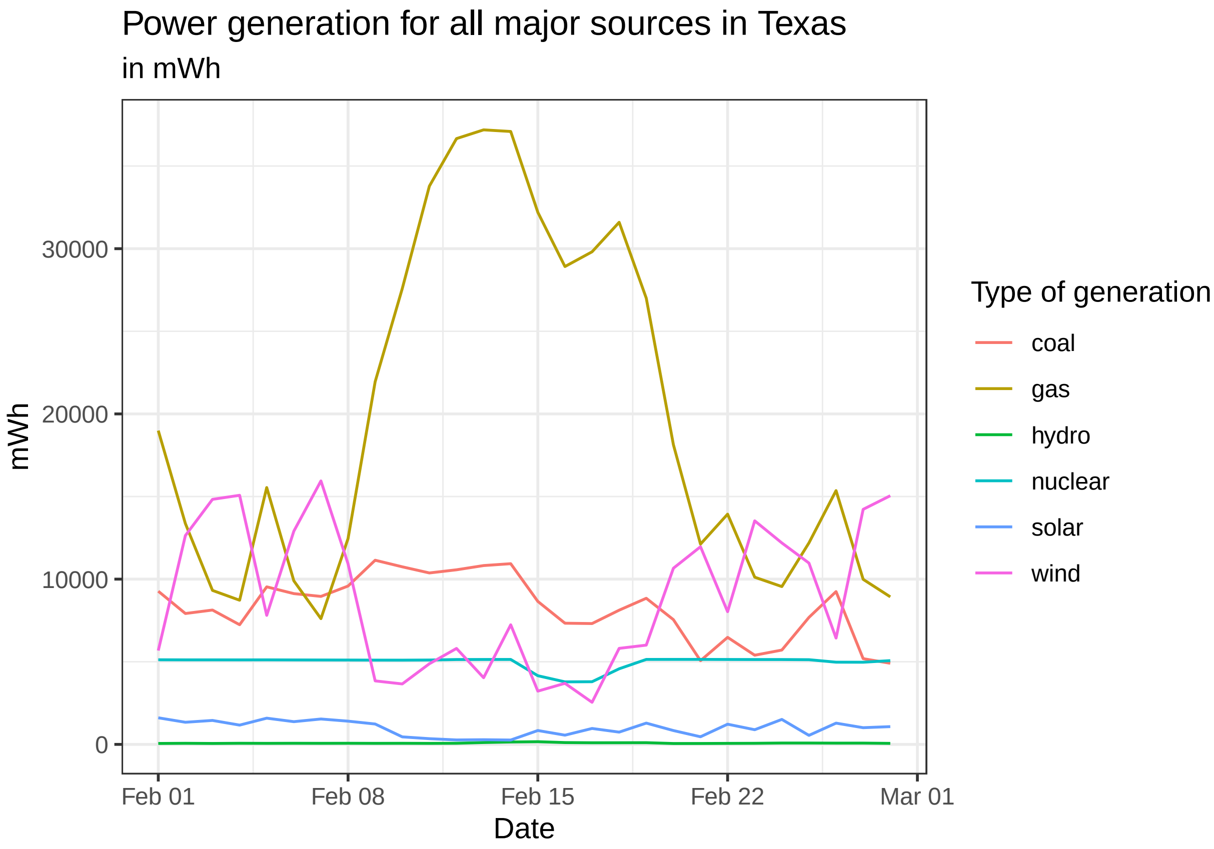
```
## Scale for 'colour' is already present. Adding another scale for 'colour',
## which will replace the existing scale.
```



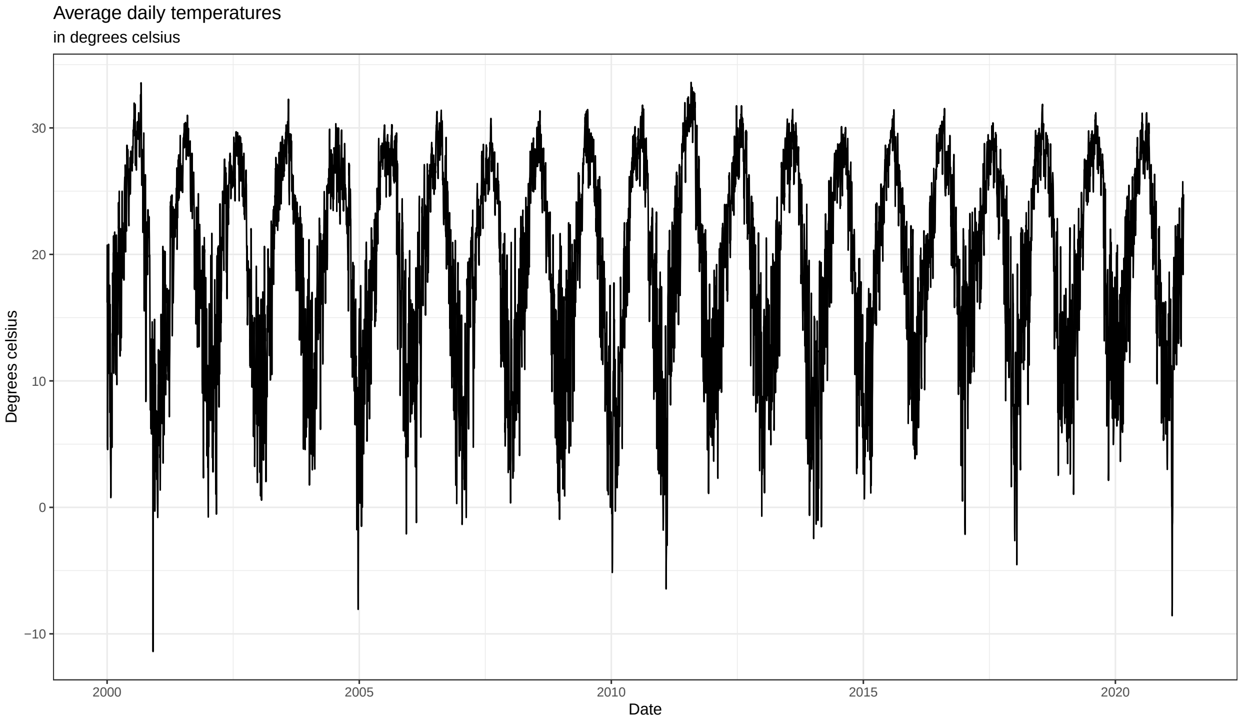
By looking at the plot above we can see that the discrepenacy between power generation and demand b

```
### Energy generation by source in february
generation_daily  %>%
  filter(month(date) == 2 &
           year(date) == 2021 &
           type %notin% c("total", "other")) %>%
  ggplot(aes(x = date, y = mWh_generated)) +
  geom_line(aes(col = type)) +
  scale_colour_manual(values = color_scheme) +
  labs(title = "Power generation for all major sources in Texas",
       subtitle = "in mWh",
       x = "Date", y = "mWh") +
  theme_bw() +
  scale_colour_discrete("Type of generation")
```

```
## Scale for 'colour' is already present. Adding another scale for 'colour',
## which will replace the existing scale.
```



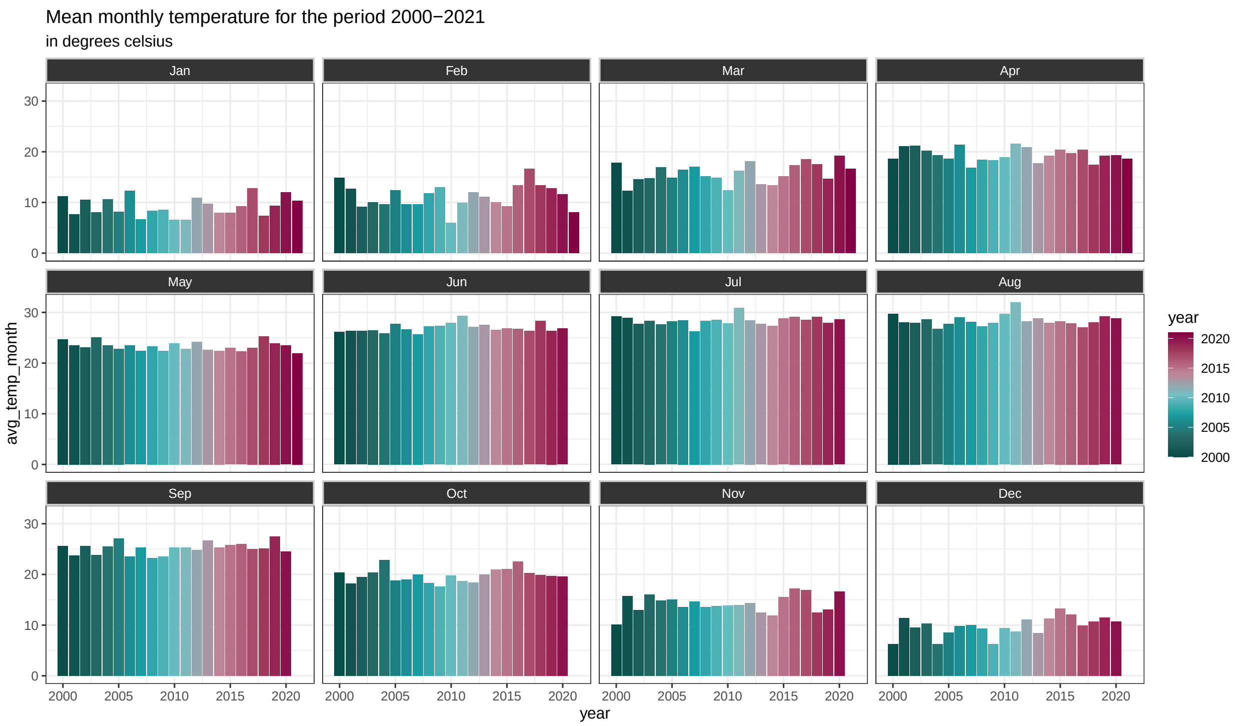
```
### Temperature averages

knitr::opts_chunk$set(fig.width=12, fig.height=8)
texas_temperature_avg   %>%
  ggplot(aes(x = date, y = temp_avg)) +
  geom_line() +
  scale_colour_manual(values = color_scheme) +
  labs(title = "Average daily temperatures",
       subtitle = "in degrees celsius",
       x = "Date", y = "Degrees celsius") +
  theme_bw()
```



Demand has changed a lot since 2000, and it begs to reason that choosing the last major cold wave gives a better representation of power demand in 2021. Based on the the last cold wave data, we will perform an arima simulation to find whether the demand ofw

```
### Temperature averages


texas_temperature_avg %>%
  mutate(year = year(date),
         month = month(date, label = TRUE),
         day = day(date)) %>%
  group_by(month, year) %>%
  summarise(avg_temp_month = mean(temp_avg)) %>%
  ggplot(aes(x = year, y = avg_temp_month, fill = year)) +
  geom_col() +
  scale_fill_hp(option = "LunaLovegood") +
  facet_wrap(~month) +
  labs(title = "Mean monthly temperature for the period 2000-2021",
       subtitle = "in degrees celsius",
       ylab = "Monthly average temperature in celsius",
       xlab = "Year") +
  theme_bw() +
  theme(
    strip.background = element_rect(fill = "grey20", color = "grey80", size = 1),
    strip.text = element_text(colour = "white")
  )
```

```
## ‘summarise()‘ has grouped output by ’month’. You can override using the ‘.groups‘ arg
```



```
arima_temperature_2011 <- texas_temperature_avg %>%
  filter(date > "2011-01-16" &
           date < "2011-02-14") %>%
  mutate(date = seq(ymd("2021-02-01"), ymd("2021-02-28"), by = "days")) %>%
  as_tsibble(index = date)



unitroot_kpss(arima_temperature_2011$temp_avg)
```

```
##   kpss_stat kpss_pvalue
##   0.2018554   0.1000000
```

Simulation of power demand: To preserve the integrity of grid connected equipment, ERCOT began load shedding on february 14th. A week previously, weather forecasts gave dire news of record-low temperatures. In combination with previous cold-weather induced power outages such as in 2011 and 1989, it begs the question about whether such a crisis could have been predicted. A report from 2011, clearly states that power outages incurred by subzero temperatures is a clear risk given the lack of winterization measures present in a large share of power generation facilities in Texas. Assuming a scenario in which power generation has been severely reduced, we can forecast demand and find whether demand at any given point surpasses the total power generation present in the Texas grid. In such a scenario, parts of the grid will have to be disconnected, leaving families without heating and power dependent businesses without revenue. This is a greatly simplified exercise, as the net generation is assumed to fall at the levels observed in 2021. This of course, cannot be known in forehand (elaborate?). ERCOT (2021) estimates the peak reduction in power generation to be around 50 000 mWh.

A multivariate forecasting model with temperature as an added predictor could be assumed to give a more accurate forecast than a univariate model using solely demand. The relationship between power demand and temperature can clearly be seen from figure (nr), in summer months (due to cooling needs) and winter months (due to heating needs). The use of a dynamic regression models as described in Hyndman(2021), allows for future assumed values of a predictor to provide more information to the model. Using this method as a basis for forecasting, we can perform a monte-carlo like simulation using simulated data based on the 2011 observed temperatures. If such a simulation is performed sufficiently many times, some information about the probability of an exceeding forecasted demand may be retrieved. Exceeding demand is defined as a case in which demand at some point in the forecasted period surpasses our assumed maximum power generation.

Using temperatures from 2011, the year in which the Groundhog Day Blizzard hit the southern states, simulated series are made using the coefficients and ARIMA orders of the fitted model.

The plot below shows the residuals of observed temperatures of the cold peak in 2011. The PACF and ACF plot show, not surprisingly, some autocorrelation at lag 1, meaning that a given observation is correlated with the immediate previous observation. A KPSS test shows that the time series is sufficiently stationary that first order differencing is not necessary.

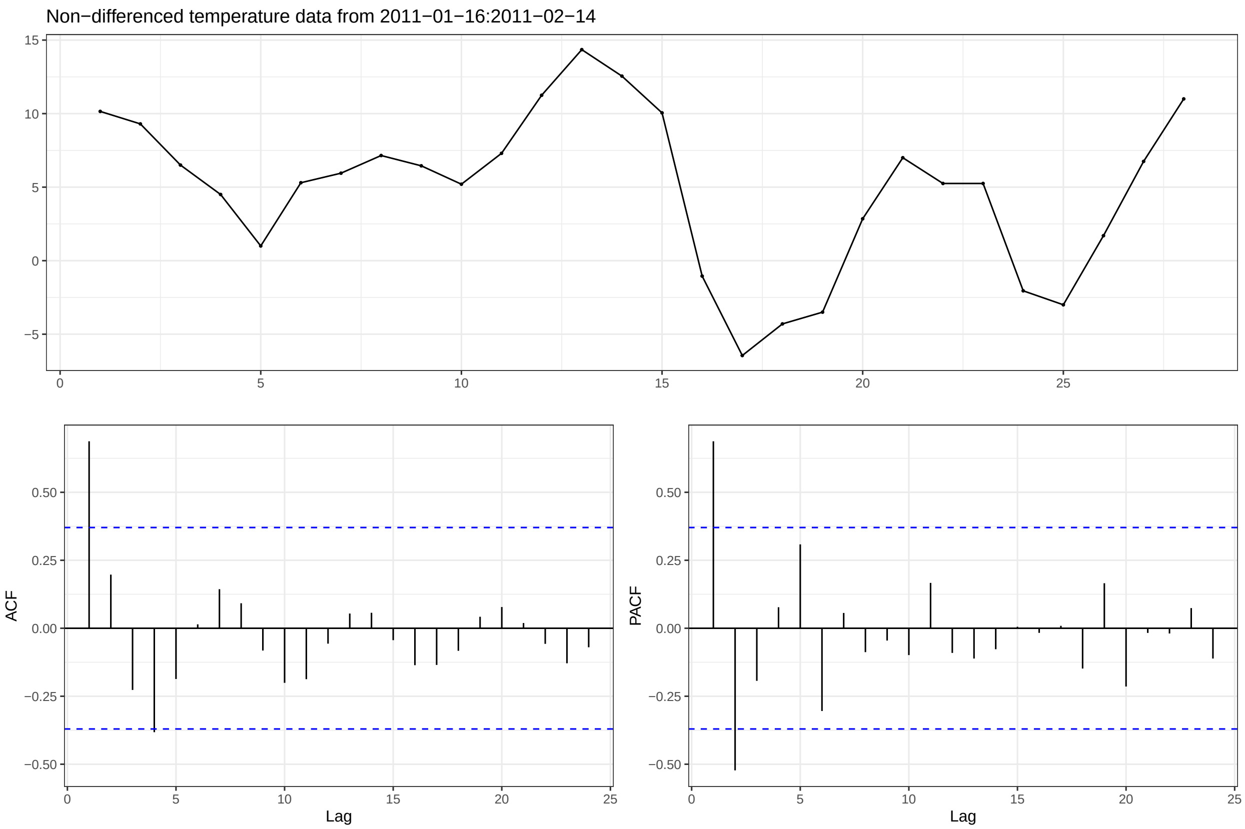
```r
# facet plot of temperature

arima_temperature_2011 <- texas_temperature_avg %>%
  filter(date > "2011-01-16" &
           date < "2011-02-14") %>%
  mutate(date = seq(ymd("2021-02-01"), ymd("2021-02-28"), by = "days")) %>%
  as_tsibble(index = date)
```

Table 4: Unitroot test on 2011 temperature data

	x
kpss_stat	0.2018554
kpss_pvalue	0.1000000

```
unitroot_kpss(arima_temperature_2011$temp_avg) %>%
  kbl(caption = "Unitroot test on 2011 temperature data") %>%
    kable_classic(full_width = F, html_font = "Times new roman")
```

```
ggtsdisplay(arima_temperature_2011$temp_avg,
            plot.type = "partial",
            lag.max = 24,
            theme = theme_bw(),
            main = "Non-differenced temperature data from 2011-01-16:2011-02-14")
```

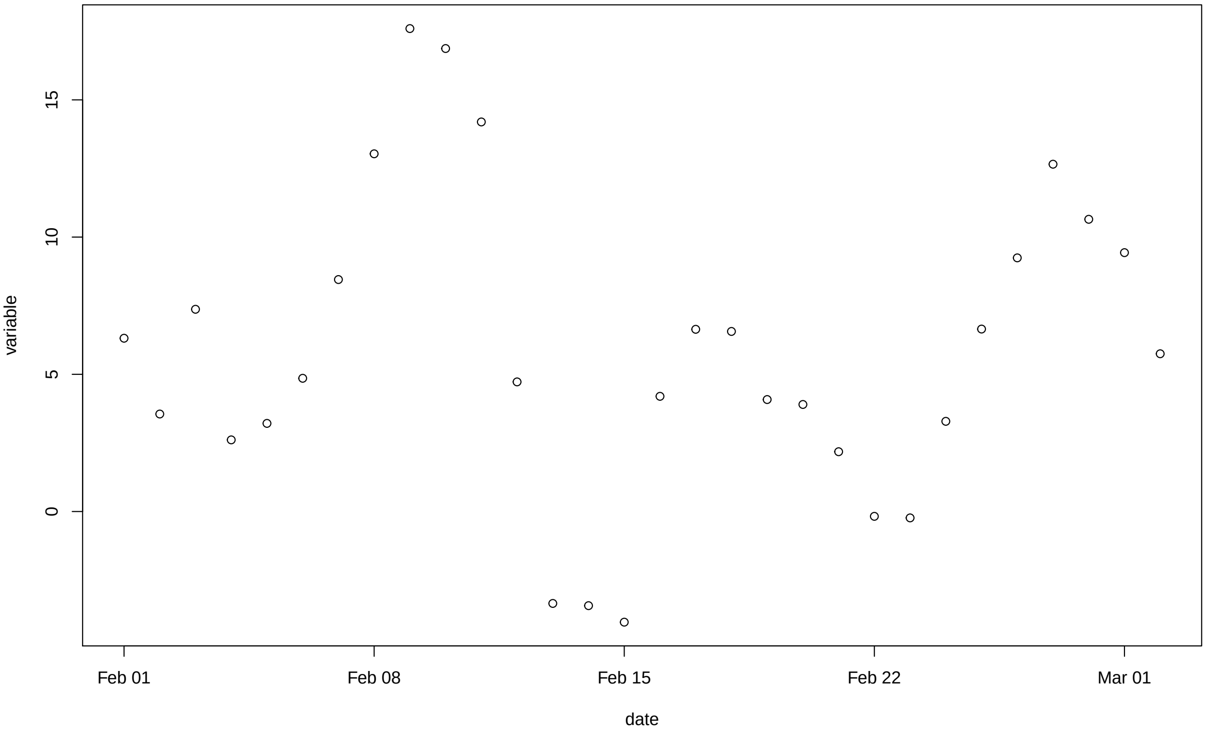


The ARIMA() function provided in the fable r package allows us to iterate through all fitted arima models and choose the optimal model based on criterias such as Akakaike Information Criterion (AIC). The fitted ARIMA model will be passed to a custom arima simulation function, which outputs a generated series based on the coefficients and ARMA orders of the series. The series will closely resemble the observed time series, but will add needed randomness in the simulation.

```
############ Fit arima series on 2011 weather data#################
fit_arima_temperature <- arima_temperature_2011 %>%
  model(arima_temperature = ARIMA(temp_avg,
                                  stepwise = FALSE,
                                  approximation = FALSE))
```

Two functions are created with the intention of generating a arima series and performing the forecast by use of a dynamic regression model.

```
arima_simulation <- function(fit,
                             days  = 30,
                             start_date = "2021-02-01")
  {
  #'Generates an optimized arima fit of based on the input dataframe
  #'on 'variable'. Based on the coefficients, AR and SMA orders, return
  #'a simulated ARIMA series. Outputs a tsibble
  #'@df : input temperature dataframe
  #'@days: simulation duration
  #'@start_date: start date of the simulation

  ar_terms = (fit %>%
                coefficients %>%
                dplyr::filter(stringr::str_detect(term,"ar")))$estimate %>%
    c(.)

  ma_terms = (fit %>%
                coefficients  %>%
                dplyr::filter(stringr::str_detect(term, "ma")))$estimate %>%
    c(.)

  constant_term = (fit %>% coefficients %>%
                     dplyr::filter(stringr::str_detect(term, "constant")))$estimate %>%
    c(.)
  if (identical(constant_term, numeric(0))) constant_term <- 0
  if (identical(ma_terms, numeric(0))) {
    arima_sim_model = list(order = fit[[1]][[1]]$fit$spec[1:3] %>%
                             t() %>% c(.),
                           ar = ar_terms)
  }
  else {
    arima_sim_model = list(order = fit[[1]][[1]]$fit$spec[1:3] %>%
                             t() %>% c(.),
                           ar = ar_terms,
                           ma = ma_terms)
  }

  sigma = sd(residuals(fit)$.resid)

  sim_arima = arima.sim(model = arima_sim_model,
                                    n = days,
                                    sd = sigma)

  return(
    data.frame(date = seq(from = ymd(start_date), length.out = length(sim_arima), by = "
              variable = sim_arima ) %>%
      mutate(variable = variable + constant_term + rnorm(n = 1, mean = 0, sd(sim_arima))
      as_tsibble(index = date))
}




arima_simulation(fit_arima_temperature) %>% plot()
```



```
forecast_sim <- function(ts,
                         fit,
                         days = 30,
                         start_date = "2020-02-01")
  {
  #' Function that performs a dynamic arima forecast based on a fitted
  #' arima series.
  #'@ts: timeseries or tsibble object of demand

  arima_sim = arima_simulation(fit, days, start_date)
  fit_demand = ts  %>%
    model(arima_dynamic_demand = ARIMA(mWh_demand_daily~variable,
                                       stepwise = TRUE,
                                       approximation = FALSE))
  fc_demand = fit_demand %>% forecast(new_data = arima_sim)
  return (fc_demand)

}
```