EXIST 2019 IDM Analysis

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1 Introduction

The main dataset is constituted of 7 different datasets which contains EXIST (Energy Exchange Istanbul) Intraday Market variables' data such as Weighted Average Price of exchanges in the market, Minimum and Maximum Prices of Bidding and Offer prices for electricity supply in the MWh scale.

Intraday Market is introduced due to the impossibility of predicting next day's hourly consumption perfectly. Unlike Day Ahead Market, there is continuous trading at Intraday Market. It is much like a stock exchange. Prices can change in mere seconds or in higher frequency. It gives an opportunity to correct participants forecasts by trading their excess or missing MWhs.

The time range of the data covers the year 2019 from January 1 to December 31. This dataset is exciting for us because the system it is based on is something different than we could. It reminds an auction which happens every hour and day, exactly like stock exchange. With this dataset, we will find the opportunity to make the deductions about how producers and consumers are imperfect in prediction their future consumption. Also, we will list the reasons of fluctuation in hourly, daily, or monthly trading in Intraday Market.

1.1 *Key Takeaways*

- Electricity prices increase when demand falls.
- Electricity usage is stable in the first six months but unstable in the last six months.

2 Summary of the Data and Explanations

Using electricity data from the EPIAS website, we obtained 2019 electricity outcomes for consumption and price. We use seven different datasets that we defined below. There are thirteen variables but one of the variables and more than 5000 rows we did not use.

- Date.Time:Date of the Process
- Hour: Hours of the Process(We will not use this variable)
- Day.Week: Days of the Process
- Month: Months of the Process
- WAP..TL.MWh.: Weighted Average Price (TL/MWH)
- Clearing.Quantity..MWh.: Clearing Quantity
- Min.Bid.Price..TL.MWh.: Minimum Demanded Price (TL/MWH)
- Max..Offer.Price..TL.MWh.: Maximum Supplied Price (TL/MWH)
- Bid.Quantity..MWh.: Demanded Quantity
- Offer.Quantity..MWh.: Supplied Quantity
- Min..Matching.Price..TL.MWh.: Minimum Matching Price (TL/MWH)
- Max..Matching.Price..TL.MWh.: Maximum Matching Price (TL/MWH)
- Trade.Value..TL.: Transaction Volume (TL)

Plan: - Cleaning and manipulating the data (Data Preprocessing) - Feature engineering the data - Visualizing the data - Revealing hidden values from the data - To be able to obey the plan, we will use some packages like:

2.1 Loading the Libraries

Throughout our analysis, we will make use of some well known R packages as tidyverse, ggplot2, lubridate, etc.

```r
library(tidyverse)
library(lubridate)
library(readr)
library(dplyr)
library(ggplot2)
library(knitr)
```

2.2 Loading Datasets

This analysis is made according to seven different datasets from Energy Exchange of Turkey (EXIST / EPIAS).

```r
weighted_average_price <- read.csv("https://github.com/pjournal/boun01g-r-sizlar/blob/gh-pages/1idm
-weighted-average-price-01012019-31122019.csv?raw=true")

matching_quantity <- read.csv("https://github.com/pjournal/boun01g-r-sizlar/blob/gh-pages/2IDMMatch
ingQuantity-01012019-31122019.csv?raw=true")

bid_prices <- read.csv("https://github.com/pjournal/boun01g-r-sizlar/blob/gh-pages/3IDMMinMaxBidPri
ces-01012019-31122019.csv?raw=true")

offer_prices <- read.csv("https://github.com/pjournal/boun01g-r-sizlar/blob/gh-pages/4IntradayMinMa
xOfferPrices-01012019-31122019.csv?raw=true")

bid_offer_quantities <- read.csv("https://github.com/pjournal/boun01g-r-sizlar/blob/gh-pages/5BidOf
ferQuantities-01012019-31122019.csv?raw=true")

matching_price <- read.csv("https://github.com/pjournal/boun01g-r-sizlar/blob/gh-pages/6IntraDayMin
MaxMatchingPrice-01012019-31122019.csv?raw=true")

trade_value <- read.csv("https://github.com/pjournal/boun01g-r-sizlar/blob/gh-pages/7IDMTradeValue-
01012019-31122019.csv?raw=true")
```

3 Data Preprocessing

To make our data ready to analyze, we will do some rearrangements on our data which will also increase its reproducibility and repeatability. These rearrangements will include:

- Joining process of all seven datasets
- Omission of some columns which we will not need to use
- Filtering of data due to necessities
- Date - Time information is converted to POSIXct format
- Adding of new columns such as Hour, Day of Week and Month

```r
alfa_data <- matching_quantity %>%
          inner_join(bid_prices, by = "Contract.Name") %>%
          inner_join(offer_prices, by = "Contract.Name") %>%
          inner_join(bid_offer_quantities, by = "Contract.Name") %>%
          inner_join(matching_price, by = "Contract.Name") %>%
          inner_join(trade_value, by = "Contract.Name") %>%
          select(-c("Contract.Type.y", "Contract.Type.x.x", "Contract.Type.y.y",
                    "Contract.Type.x.x.x", "Contract.Type.y.y.y", "Contract.Name")) %>%
          filter(Contract.Type.x == "Hourly") %>%
          select(-Contract.Type.x)

alfa_data %>%
  glimpse()
```

```
## Rows: 8,740
## Columns: 10
## $ Clearing.Quantity..MWh.       <chr> "331.20", "527.70", "196.70", "414.70"...
## $ Min.Bid.Price..TL.MWh.        <dbl> 5.00, 5.00, 41.00, 1.00, 1.00, 1.00, 1...
## $ Max..Bid.Price..TL.MWh.       <chr> "101.38", "97.55", "81.60", "45.00", "...
## $ Min..Offer.Price..TL.MWh.     <chr> "60.00", "93.82", "40.00", "4.00", "5....
## $ Max..Offer.Price..TL.MWh.     <chr> "100.39", "296.29", "81.60", "45.00", ...
## $ Bid.Quantity..MWh.            <chr> "392.50", "910.00", "576.70", "797.40"...
## $ Offer.Quantity..MWh.          <chr> "509.40", "664.20", "349.60", "552.90"...
## $ Min..Matching.Price..TL.MWh.  <dbl> 60.00, 93.82, 41.05, 4.00, 5.00, 5.00,...
## $ Max..Matching.Price..TL.MWh.  <dbl> 100.39, 97.55, 81.60, 45.00, 11.52, 11...
## $ Trade.Value..TL.              <chr> "33,182.96", "51,036.02", "15,652.36",...
```

```
beta_data <- weighted_average_price %>%
  bind_cols(alfa_data)

beta_data %>%
  glimpse()
```

```
## Rows: 8,740
## Columns: 13
## $ Date                          <chr> "01.01.2019", "01.01.2019", "01.01.201...
## $ Hour                          <chr> "00:00", "01:00", "02:00", "03:00", "0...
## $ WAP..TL.MWh.                  <dbl> 100.23, 96.85, 80.25, 38.28, 11.67, 11...
## $ Clearing.Quantity..MWh.       <chr> "331.20", "527.70", "196.70", "414.70"...
## $ Min.Bid.Price..TL.MWh.        <dbl> 5.00, 5.00, 41.00, 1.00, 1.00, 1.00, 1...
## $ Max..Bid.Price..TL.MWh.       <chr> "101.38", "97.55", "81.60", "45.00", "...
## $ Min..Offer.Price..TL.MWh.     <chr> "60.00", "93.82", "40.00", "4.00", "5....
## $ Max..Offer.Price..TL.MWh.     <chr> "100.39", "296.29", "81.60", "45.00", ...
## $ Bid.Quantity..MWh.            <chr> "392.50", "910.00", "576.70", "797.40"...
## $ Offer.Quantity..MWh.          <chr> "509.40", "664.20", "349.60", "552.90"...
## $ Min..Matching.Price..TL.MWh.  <dbl> 60.00, 93.82, 41.05, 4.00, 5.00, 5.00,...
## $ Max..Matching.Price..TL.MWh.  <dbl> 100.39, 97.55, 81.60, 45.00, 11.52, 11...
## $ Trade.Value..TL.              <chr> "33,182.96", "51,036.02", "15,652.36",...
```

```
Sys.setlocale("LC_TIME", "C")
```

```
## [1] "C"
```

```
idm_data <- beta_data %>%
  mutate(Date.Time = as.POSIXlt(factor(Date), format="%d.%m.%y")) %>%
  mutate(Date.Time = update(Date.Time, year = 2019)) %>%
  mutate(Day.Week = wday(Date.Time,label = TRUE,week_start=1), Month = month(Date.Time),Hour = hour
(Date.Time)) %>%
  select(-Date) %>%
  relocate(Date.Time,
  Hour,
          Day.Week,
          Month,
          WAP..TL.MWh.,
          Clearing.Quantity..MWh.,
          Min.Bid.Price..TL.MWh.,
          Max..Offer.Price..TL.MWh.,
          Bid.Quantity..MWh.,
          Offer.Quantity..MWh.,
          Min..Matching.Price..TL.MWh.,
          Max..Matching.Price..TL.MWh.,
          Trade.Value..TL.)
idm_data$Hour <- replace(idm_data$Hour, values = 0:23)
idm_data %>% glimpse()
```

```
## Rows: 8,740
## Columns: 15
## $ Date.Time                  <dttm> 2019-01-01, 2019-01-01, 2019-01-01, 2...
## $ Hour                       <int> 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, ...
## $ Day.Week                   <ord> Tue, Tue, Tue, Tue, Tue, Tue, Tue, Tue...
## $ Month                      <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,...
## $ WAP..TL.MWh.               <dbl> 100.23, 96.85, 80.25, 38.28, 11.67, 11...
## $ Clearing.Quantity..MWh.    <chr> "331.20", "527.70", "196.70", "414.70"...
## $ Min.Bid.Price..TL.MWh.     <dbl> 5.00, 5.00, 41.00, 1.00, 1.00, 1.00, 1...
## $ Max..Offer.Price..TL.MWh.  <chr> "100.39", "296.29", "81.60", "45.00", ...
## $ Bid.Quantity..MWh.         <chr> "392.50", "910.00", "576.70", "797.40"...
## $ Offer.Quantity..MWh.       <chr> "509.40", "664.20", "349.60", "552.90"...
## $ Min..Matching.Price..TL.MWh. <dbl> 60.00, 93.82, 41.05, 4.00, 5.00, 5.00,...
## $ Max..Matching.Price..TL.MWh. <dbl> 100.39, 97.55, 81.60, 45.00, 11.52, 11...
## $ Trade.Value..TL.           <chr> "33,182.96", "51,036.02", "15,652.36",...
## $ Max..Bid.Price..TL.MWh.    <chr> "101.38", "97.55", "81.60", "45.00", "...
## $ Min..Offer.Price..TL.MWh.  <chr> "60.00", "93.82", "40.00", "4.00", "5....
```

```r
idm_data$Clearing.Quantity..MWh. <- as.numeric(idm_data$Clearing.Quantity..MWh.)
idm_data$Max..Bid.Price..TL.MWh. <- as.numeric(idm_data$Max..Bid.Price..TL.MWh.)
idm_data$Max..Offer.Price..TL.MWh. <- as.numeric(idm_data$Max..Offer.Price..TL.MWh.)
idm_data$Bid.Quantity..MWh. <- as.numeric(idm_data$Bid.Quantity..MWh.)
idm_data$Offer.Quantity..MWh. <- as.numeric(idm_data$Offer.Quantity..MWh.)
idm_data$Trade.Value..TL. <- as.numeric(gsub(",", "", idm_data$Trade.Value..TL.))
idm_data[is.na(idm_data)] <- 0
```
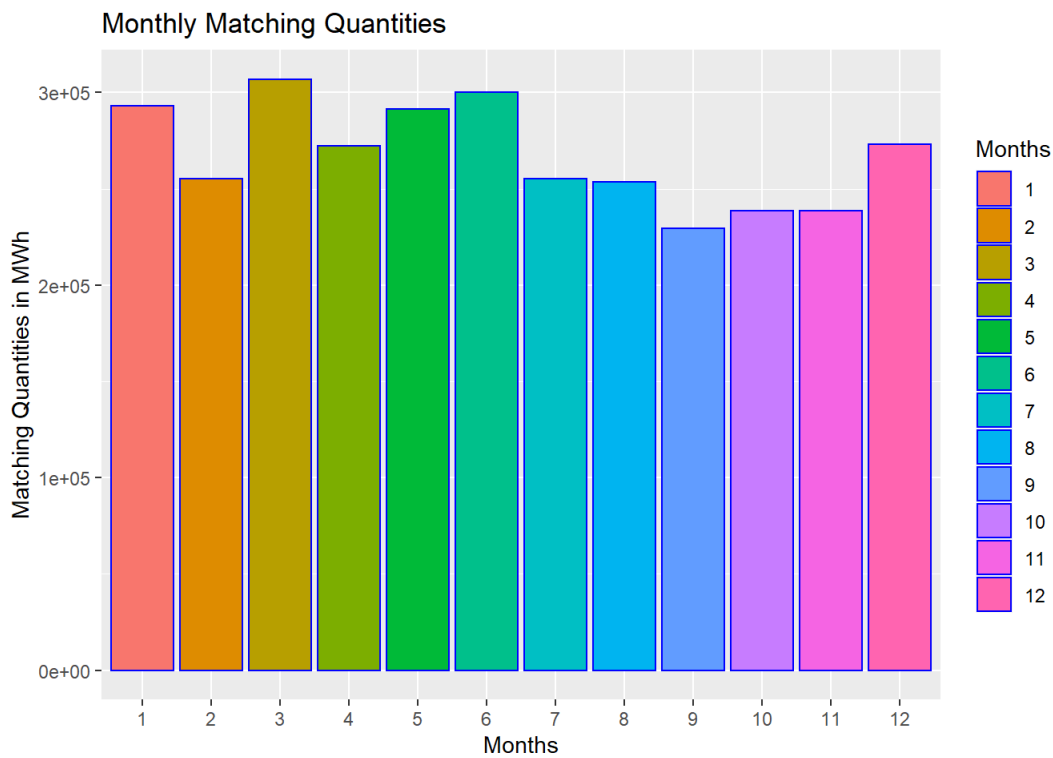
4 Exploratory Data Analysis

4.1 IDM Matching Quantity

In this part we made monthly comparison of IDM matching quantities for 2019.

```r
new_dataa <- idm_data %>% select(Month,Clearing.Quantity..MWh.)
monthly_matching_quantity <- new_dataa %>% group_by(Month) %>% summarise(Clearing.Quantity..MWh.= sum(Clearing.Quantity..MWh.))

ggplot(data=monthly_matching_quantity,aes(x=as.factor(Month),y=Clearing.Quantity..MWh.,fill=as.factor(Month)))+
labs(x="Months", y="Matching Quantities in MWh", color="Months", title = "Monthly Matching Quantities") +
  geom_bar(stat='identity',width=0.9,color='blue') +
  guides(fill=guide_legend(title="Months"))
```

Monthly Matching Quantities

As seen above, the Matching Quantity has a peak in March and a minimum point in September. Matching Quantity increases in Winter and decreases in Summer, because in Summertime, due to holidays and entertainment usages, electricity price is harder to predict. However, in Winter, customers can predict the price easily.
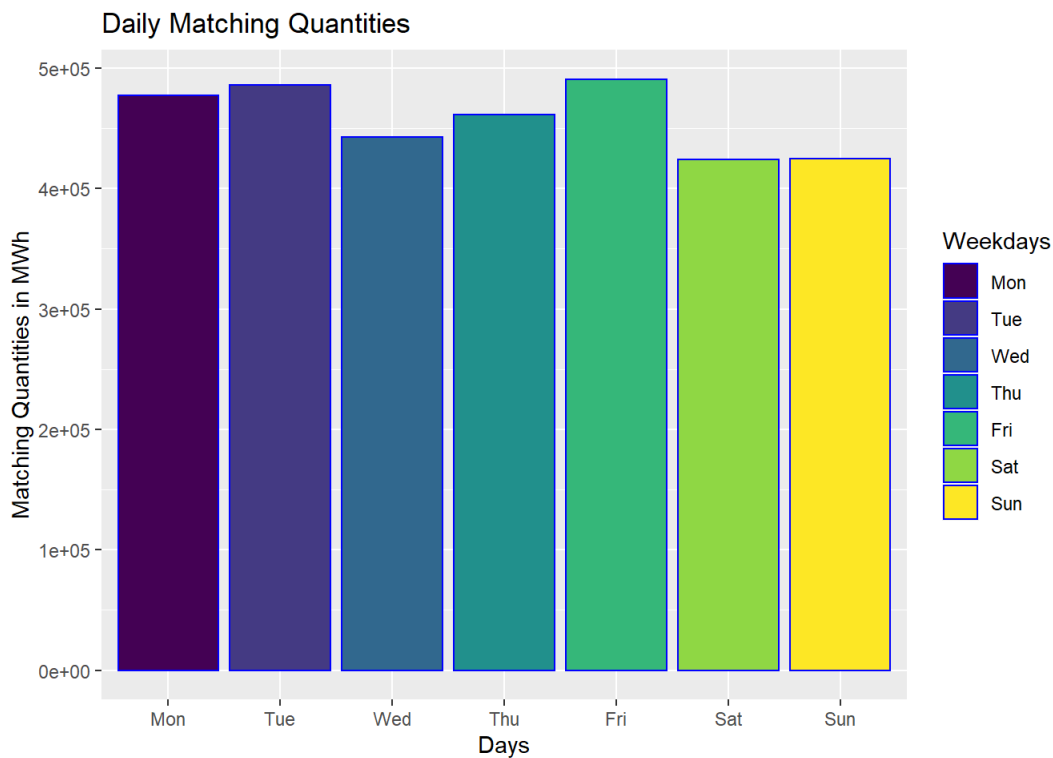
4.2 IDM Daily Matching Quantities

In this part we made daily comparison of IDM matching quantities for 2019.

```
new_dataa2 <- idm_data %>% select(Clearing.Quantity..MWh.,Day.Week)
daily_matching_quantity <- new_dataa2 %>% group_by(Day.Week) %>% summarise(Clearing.Quantity..MWh.=
sum(Clearing.Quantity..MWh.))

ggplot(data=daily_matching_quantity,aes(x=as.factor(Day.Week),y=Clearing.Quantity..MWh.,fill=as.fac
tor(Day.Week)))+
labs(x="Days", y="Matching Quantities in MWh", color="Days", title = "Daily Matching Quantities") +

  geom_bar(stat='identity',width=0.9,color='blue') +
  guides(fill=guide_legend(title="Weekdays"))
```

Daily Matching Quantities

According to the plot above, there is no significant differences in the Matching Quantities in the weekdays.However, a little drop can be seen in the weekend. Matching Quantity increases in Weekdays and decreases in Weekend, because in Weekend, due to holidays and entertainment usages, electricity price is harder to predict. However, in Weekdays, customers can predict the price easily.
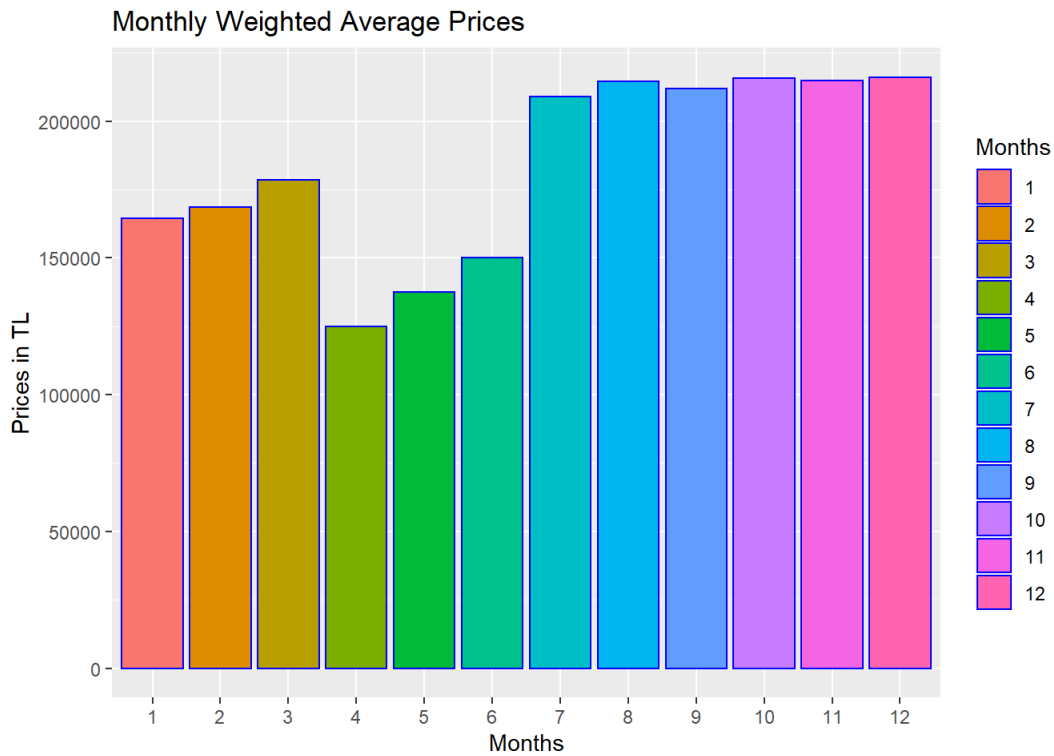
4.3 IDM Monthly Weighted Average Prices

In this part we made monthly comparison of IDM weighted average prices for 2019.

```
new_dataa3 <- idm_data %>% select(WAP..TL.MWh.,Month)
monthly_weighted_average_prices <- new_dataa3 %>% group_by(Month) %>% summarise(WAP..TL.MWh.= sum(W
AP..TL.MWh.))

a <- ggplot(monthly_weighted_average_prices,aes(x=as.factor(Month),y=WAP..TL.MWh.,fill=as.factor(Mo
nth)))+
labs(x="Months", y="Prices in TL", color="Months", title = "Monthly Weighted Average Prices") +
  geom_bar(stat='identity',width=0.9,color='blue') +
  guides(fill=guide_legend(title="Months"))

show(a)
```

Monthly Weighted Average Prices

The reason for the decrease in the first two quarters is the intensive use of electricity due to the workload and weather conditions in winter. As seen above, in the second half of the year Monthly Weighted Average Prices went up. In the last two quarters, prices have increased due to low electricity usage.
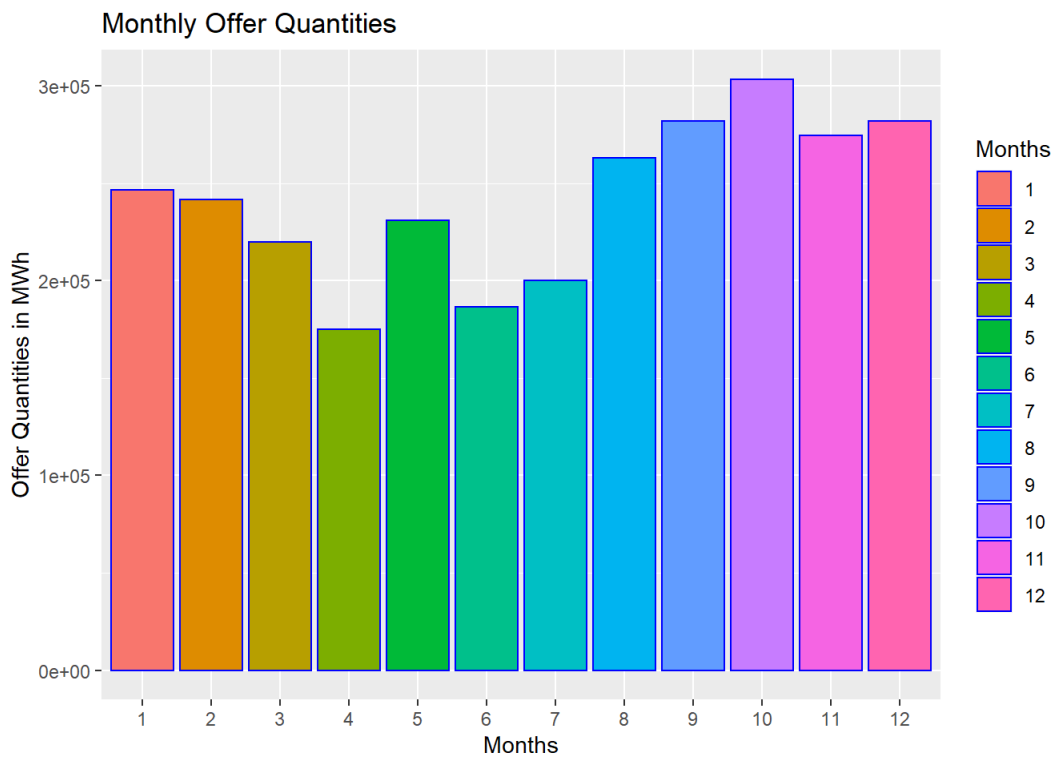
4.4 IDM Monthly Offer Quantities

In this part we made monthly comparison of IDM monthly offer quantities for 2019.

```
new_dataa4 <- idm_data %>% select(Offer.Quantity..MWh.,Month)
monthly_offer_quantities <- new_dataa4 %>% group_by(Month) %>% summarise(Offer.Quantity..MWh.= sum(
Offer.Quantity..MWh.))

ggplot(monthly_offer_quantities,aes(x=as.factor(Month),y=Offer.Quantity..MWh.,fill=as.factor(Month)
))+
labs(x="Months", y="Offer Quantities in MWh", color="Months", title = "Monthly Offer Quantities") +

  geom_bar(stat='identity',width=0.9,color='blue') +
  guides(fill=guide_legend(title="Months"))
```

Monthly Offer Quantities

It can be seen that there is a reduction in the offer quantities in the beginning of the year till May. After that, we can see significantly higher offer quantities in the last quarter. Since the use of electricity will increase with the start of school and work intensity at the end of the holiday period, Offer Quantities went up.

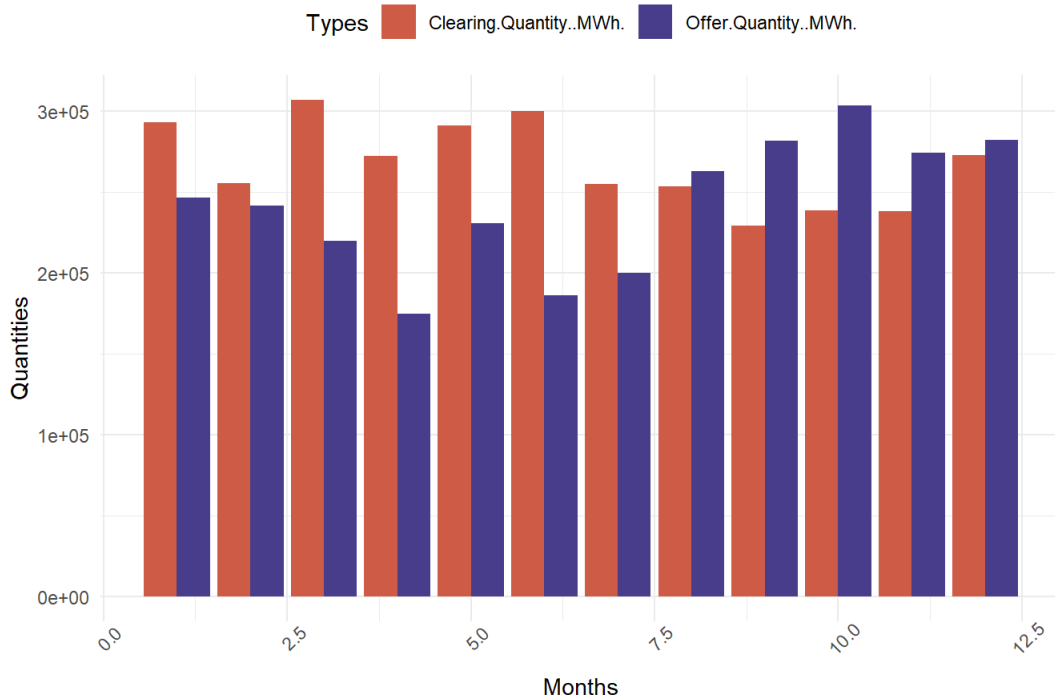# 4.5 IDM Monthly Offer and Matching Quantities

In this part we made monthly comparison of IDM offer and matching quantities for 2019.

```
new_dataa5 <- idm_data %>% select(Month,Clearing.Quantity..MWh.,Offer.Quantity..MWh.)
monthly_offer_and_matching_quantities <- new_dataa5 %>% group_by(Month) %>% summarise(Clearing.Quan
tity..MWh.= sum(Clearing.Quantity..MWh.),Offer.Quantity..MWh.=sum(Offer.Quantity..MWh.))

monthly_offer_and_matching_quantities_longer <-
monthly_offer_and_matching_quantities %>%
  ungroup() %>%
  pivot_longer(cols=c(Clearing.Quantity..MWh., Offer.Quantity..MWh.), names_to="Types", values_to="
Quantities") %>%
  select(Month,Types,Quantities)

ggplot(monthly_offer_and_matching_quantities_longer, aes(x=Month, y=Quantities, fill=Types)) +
          scale_fill_manual(values=c("coral3", "darkslateblue")) +
          theme_minimal() +
          geom_bar(stat="identity", position="dodge") +
          ggtitle("Average Matching vs Offer Quantities per Month") +
          theme(axis.text.x = element_text(angle = 45), legend.position = "top")+
          labs(x="Months")
```

Average Matching vs Offer Quantities per Month

In the third quarter, because of the work and school intensity, increase in the offer quantity is usual.

4.6 IDM Monthly Maximum Bid and Matching Prices

We compared IDM maximum bid, and matching prices for 2019.

```
new_dataa9 <- idm_data %>% select(Month,Max..Matching.Price..TL.MWh., Max..Bid.Price..TL.MWh.)
monthly_max_offer_and_matching_bid_prices <- new_dataa9 %>% group_by(Month) %>% summarise(Max..Matc
hing.Price..TL.MWh.=sum(Max..Matching.Price..TL.MWh.), Max..Bid.Price..TL.MWh.=sum( Max..Bid.Price.
.TL.MWh.))

monthly_max_offer_and_matching_bid_prices_longer <-
monthly_max_offer_and_matching_bid_prices %>%
  ungroup() %>%
  pivot_longer(cols=c( Max..Matching.Price..TL.MWh.,Max..Bid.Price..TL.MWh.), names_to="Types", val
ues_to="Prices") %>%
  select(Month,Types,Prices)

ggplot(monthly_max_offer_and_matching_bid_prices_longer, aes(x=as.factor(Month), y=Prices, fill=Typ
es)) +
          scale_fill_manual(values=c("coral3", "darkslateblue")) +
          theme_minimal() +
          geom_bar(stat="identity", position="dodge") +
          ggtitle("IDM Monthly Maximum Matching Prices and Bid Prices") +
          theme(axis.text.x = element_text(angle = 0), legend.position = "top")+
          labs(x="Months")
```

IDM Monthly Maximum Matching Prices and Bid Prices
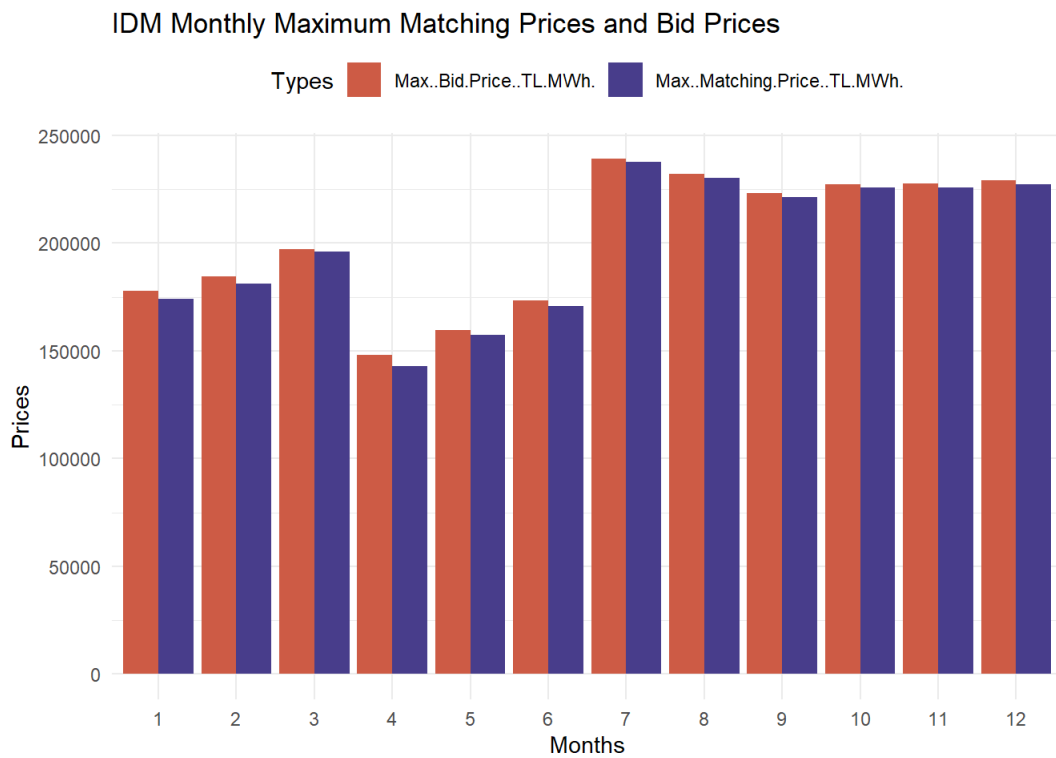
According to our analyses shown above, in the second quarter there is a significant drop in both prices. Moreover, to compare prices to each other, we can see that maximum bid prices are slightly higher than maximum matching prices. The maximum offered price is expected to be close to the accepted price. So, we can see that the Maximum Bid Prices and the Maximum Matching Prices are always close.
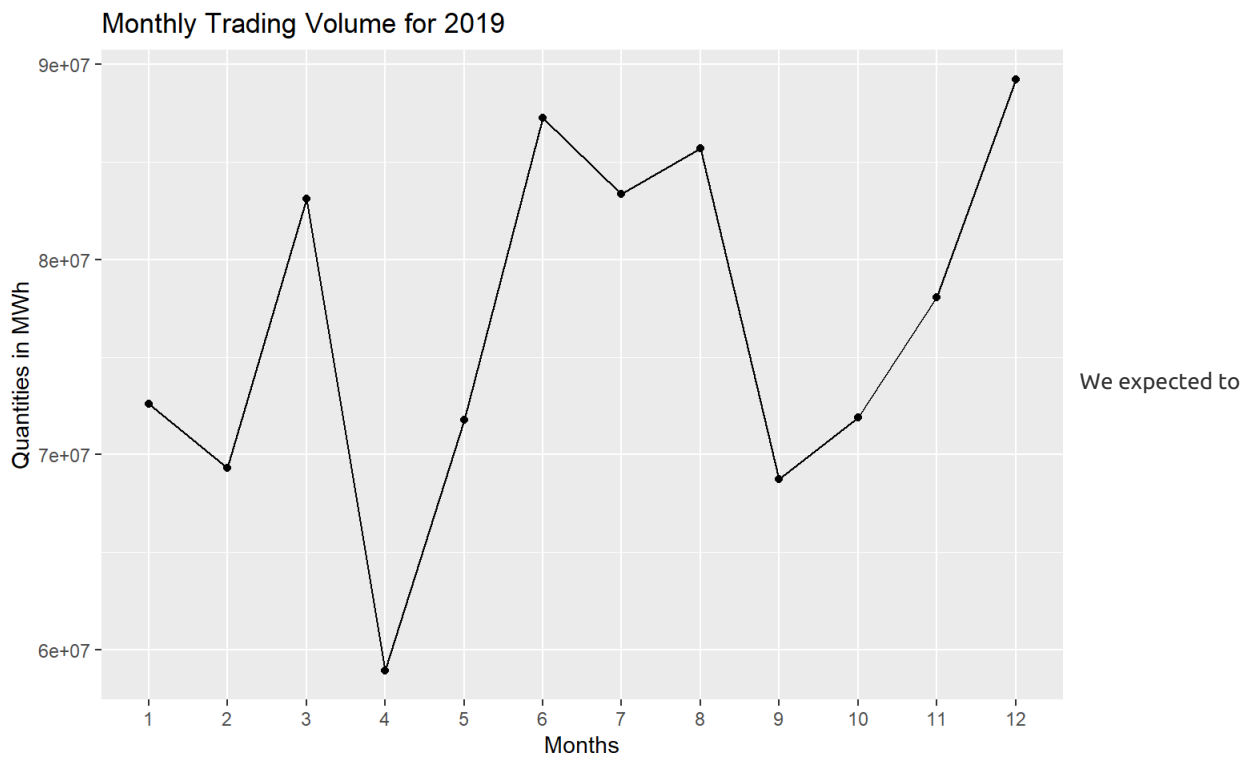
4.7 IDM Monthly Trading Volume

In this part we made monthly comparison of IDM traing volume for 2019.

```
new_dataa6 <- idm_data %>% select(Month,Trade.Value..TL.)

monthly_trading_volume <- new_dataa6 %>%
  group_by(Month) %>%
  summarise(Trade.Value..TL.= sum(Trade.Value..TL.))

ggplot(data=monthly_trading_volume,aes(x=as.factor(Month),y=Trade.Value..TL., group = 1)) +
  geom_line() +
  geom_point() +
  labs(
    title = "Monthly Trading Volume for 2019",
    x = "Months",
    y = "Quantities in MWh"
  )
```

Monthly Trading Volume for 2019

We expected to see significant and meaningful values and changes in the total trading volume graph. However, we see no correlation between monthly trading volume values.

5 Conclusion

First of all, we analyzed daily and monthly electricity prices and usage amounts. In addition, we analyzed the maximum and minimum bid and match prices. Based on these, we see that electricity prices depend on electricity usage. Furthermore, the use of electricity also changes according to the seasons and months. The main reasons for this are the customers' school intensity, work intensity and holiday periods.

6 References

- Energy Exchange of Turkey (EXIST / EPIAS)
- ANNUAL REPORT 2017(EXIST / EPIAS)