

Forecast of Electricity Consumption

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Introduction

Electricity is the only commodity that is produced and consumed simultaneously; therefore, a perfect balance between supply and consumption in the electricity power market must always be maintained. Forecasting electricity consumption is of national interest to any country since electricity is a key source of energy. A reliable forecast of energy consumption, production, and distribution meets the stable and long-term policy. The presence of economies of scale, focus on environmental concerns, regulatory requirements, and a favorable public image, coupled with inflation, rapidly rising energy prices, the emergence of alternative fuels and technologies, changes in life styles, and so on, has generated the need to use modeling techniques which capture the effect of factors such as prices, income, population, technology, and other economic, demographic, policy, and technological variables.

Underestimation could lead to under-capacity utilization, which would result in poor quality of service including localized brownouts, or even blackouts. While on the other hand, an overestimation could lead to the authorization of a plant that may not be needed for several years. The requirement is to ensure optimal phasing of investments, a long-term consideration, and rationalizing pricing structures and designing demand-side management programs, to meet the nature of short- or medium-term needs. The forecast further drives various plans and decisions on investment, construction, and conservation.

In order to carry out forecasting of electricity consumption, we shall be using a dataset collected on smart meter data with time series aggregated by four located industries.

Collecting and describing data

The dataset titled `DT_4_ind` shall be used. The numeric variable is as follows:

- `value`

The non-numeric variables are as follows:

- `date_time`
- `week`
- `date`
- `type`

Exploring data

The following packages need to be loaded as a first step to be carried out:

```
> install.packages("feather")
> install.packages("data.table")
> install.packages("ggplot2")
> install.packages("plotly")
> install.packages("animation")
> library(feather)
> library(data.table)
> library(ggplot2)
> library(plotly)
> library(animation)
```

Regression analysis

The regression model is formulated as follows:

$$y_i = \beta_1 d_{i1} + \beta_2 d_{i2} + \dots + \beta_{48} d_{i48} + \beta_{49} w_{i1} + \dots + \beta_{54} w_{i6} + \varepsilon_i$$

Variables (inputs) are of two types of seasonal dummy variables--daily (d_1, \dots, d_{48}) and weekly (w_1, \dots, w_6). y_i is the electricity consumption at the time i , where $i = 1, \dots, N$. $\beta_1 \dots \beta_{54}$ are the regression coefficients to be estimated.

Printing the contents of the AggData data frame:

```
> AggData
```

The result is as follows:

	date_time	value	week	date	type
1:	2012-01-02 00:00:00	1590.210	Monday	2012-01-02	Commercial Property
2:	2012-01-02 00:30:00	1563.772	Monday	2012-01-02	Commercial Property
3:	2012-01-02 01:00:00	1559.914	Monday	2012-01-02	Commercial Property
4:	2012-01-02 01:30:00	1584.671	Monday	2012-01-02	Commercial Property
5:	2012-01-02 02:00:00	1604.281	Monday	2012-01-02	Commercial Property

70076:	2012-12-31 21:30:00	3548.279	Monday	2012-12-31	Light Industrial
70077:	2012-12-31 22:00:00	3488.161	Monday	2012-12-31	Light Industrial
70078:	2012-12-31 22:30:00	3510.200	Monday	2012-12-31	Light Industrial
70079:	2012-12-31 23:00:00	3533.678	Monday	2012-12-31	Light Industrial
70080:	2012-12-31 23:30:00	3414.966	Monday	2012-12-31	Light Industrial

Transforming the characters of weekdays to integers: The `as.factor()` function is used to encode a vector as a factor. The `as.integer()` function creates the `AggData[, week]` object of the integer type:

```
> AggData[, week_num := as.integer(as.factor(AggData[, week]))]
```

Printing the contents of the AggData data frame after the change:

```
> AggData
```

As is clearly visible, the points are not normal as they are away from the red line. The measurements during the day were moved constantly by the estimated coefficient of the week variable, but the behavior during the day wasn't captured. We need to capture this behavior because weekends, especially, behave absolutely differently.

Improving regression analysis

Creating a linear model: The `lm()` function fits the linear models. `Load ~ 0 + Daily + weekly + Daily:weekly` is the new formula. Since `lm()` automatically adds to the linear model intercept, we define it now as 0. `data = matrix_train` defines the data frame which contains the data:

```
> linear_model_2 <- lm(Load ~ 0 + Daily + weekly + Daily:weekly, data =
matrix_train)
```

Printing the contents of the `linear_model_2` data frame after the change:

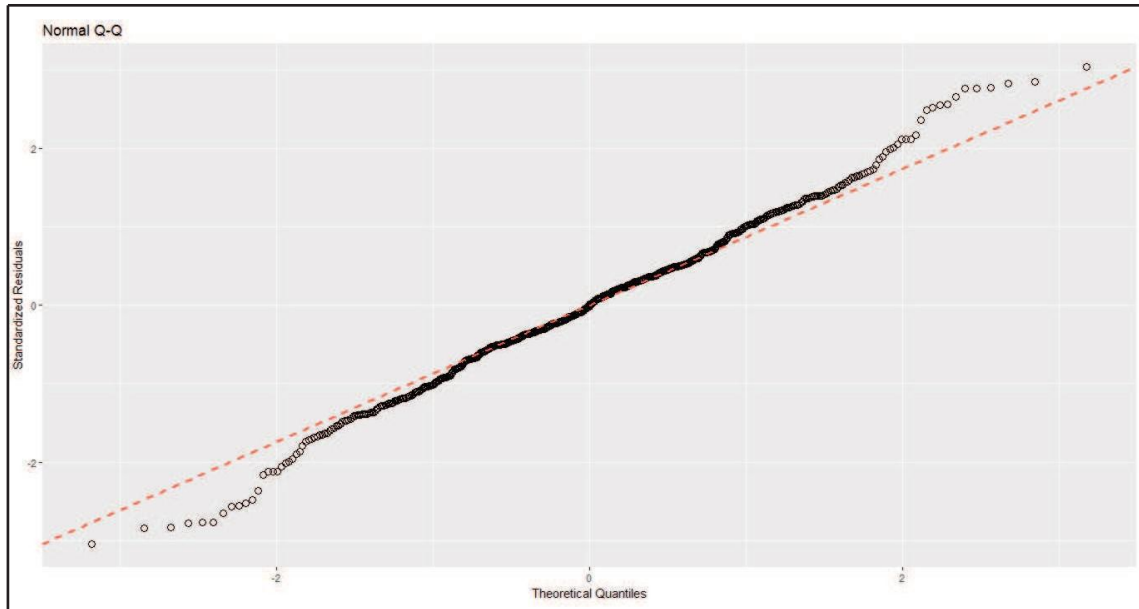
```
> linear_model_2
```

The result is as follows:

```
Call:
lm(formula = Load ~ 0 + Daily + weekly + Daily:weekly, data = matrix_train)

Coefficients:
    Daily1      Daily2      Daily3      Daily4      Daily5      Daily6      Daily7
  963.6868    910.1281    832.4827    767.9888    746.0964    709.4052    646.7310
    Daily8      Daily9      Daily10     Daily11     Daily12     Daily13     Daily14
  607.0952    593.1229    579.3818    571.4749    577.7818    575.1910    576.0727
    Daily15     Daily16     Daily17     Daily18     Daily19     Daily20     Daily21
  590.8817    596.6877    599.9783    596.8332    605.5058    617.2628    685.2319
    Daily22     Daily23     Daily24     Daily25     Daily26     Daily27     Daily28
  742.3322    951.7756    1158.7365    1339.7397    1530.8187    1680.5525    1772.6732
    Daily29     Daily30     Daily31     Daily32     Daily33     Daily34     Daily35
  1812.0905    1827.8779    1834.1506    1869.0104    1875.9046    1860.0126    1846.6024
    Daily36     Daily37     Daily38     Daily39     Daily40     Daily41     Daily42
  1789.6251    1731.6673    1682.2293    1586.0122    1571.6402    1496.8899    1358.2929
    Daily43     Daily44     Daily45     Daily46     Daily47     Daily48     weekly
  1245.7848    1166.1215    1091.9825    1066.7010    997.4765    955.2032    -355.3522
    weekly3     weekly4     weekly5     weekly6     weekly7     Daily2:weekly2   Daily3:weekly2
   -42.9479    -383.8207    -47.4477     43.1739     38.2679     46.9318     138.6611
    Daily4:weekly2   Daily5:weekly2   Daily6:weekly2   Daily7:weekly2   Daily8:weekly2   Daily9:weekly2   Daily10:weekly2
    211.0272     238.7233     273.2973     342.3193     382.9568     393.0218     420.0024
    Daily11:weekly2   Daily12:weekly2   Daily13:weekly2   Daily14:weekly2   Daily15:weekly2   Daily16:weekly2   Daily17:weekly2
    433.0777     432.5059     439.6293     428.7760     429.8100     424.0835     429.2114
    Daily18:weekly2   Daily19:weekly2   Daily20:weekly2   Daily21:weekly2   Daily22:weekly2   Daily23:weekly2   Daily24:weekly2
    441.2555     483.8489     489.4588     450.5552     461.8552     547.1952     614.2202
    Daily25:weekly2   Daily26:weekly2   Daily27:weekly2   Daily28:weekly2   Daily29:weekly2   Daily30:weekly2   Daily31:weekly2
    635.9273     645.8638     629.4519     538.6554     531.7929     506.9881     510.5959
    Daily32:weekly2   Daily33:weekly2   Daily34:weekly2   Daily35:weekly2   Daily36:weekly2   Daily37:weekly2   Daily38:weekly2
    516.8237     507.8630     524.8920     514.2205     531.7239     513.5249     515.8282
    Daily39:weekly2   Daily40:weekly2   Daily41:weekly2   Daily42:weekly2   Daily43:weekly2   Daily44:weekly2   Daily45:weekly2
    603.7991     572.5889     557.3761     561.1792     551.5947     539.1175     529.6320
    Daily46:weekly2   Daily47:weekly2   Daily48:weekly2   Daily49:weekly2   Daily50:weekly2   Daily51:weekly2   Daily52:weekly2
    491.0887     477.7638     443.8735     5.5692     10.2973     32.1318     32.9816
```

The result is as follows:



Building a forecasting model

We can define a function to return the forecast for a 1 week ahead prediction. The input parameters are data and set_of_date:

```
> predWeekReg <- function(data, set_of_date){  
+ #creating the dataset by dates  
+ data_train <- data[date %in% set_of_date]  
+ N <- nrow(data_train)  
+  
+ # number of days in the train set  
+ window <- N / period # number of days in the train set  
+  
+ #1, ..., period, 1, ..., period - daily season periods  
+ #feature "week_num"- weekly season  
+ matrix_train <- data.table(Load = data_train[, value],  
+ Daily = as.factor(rep(1:period, window)),  
+ Weekly = as.factor(data_train[, week_num]))  
+  
+ #creating linear model.  
+ # formula - Load ~ 0 + Daily + Weekly + Daily:Weekly  
+ # dataset - data = matrix_train
```

Plotting the forecast for a year

Plotting the results:

```
> datas <- data.table(value = c(as.vector(lm_pred_weeks_1),
  AggData[(type == n_type[1]) & (date %in% n_date[-c(1:14,365)]),
value]),
  date_time = c(rep(AggData[-c(1:(14*48), (17473:nrow(AggData))),
date_time], 2)),
  type = c(rep("MLR", nrow(lm_pred_weeks_1)*ncol(lm_pred_weeks_1)),
rep("Real", nrow(lm_pred_weeks_1)*ncol(lm_pred_weeks_1))),
  week = c(rep(1:50, each = 336), rep(1:50, each = 336)))

> saveGIF({
  oopt = ani.options(interval = 0.9, nmax = 50)
  for(i in 1:ani.options("nmax")){
    print(ggplot(data = datas[week == i], aes(date_time, value, group =
type, colour = type)) +
      geom_line(size = 0.8) +
      scale_y_continuous(limits = c(min(datas[, value]), max(datas[,
value])))) +
      theme(panel.border = element_blank(), panel.background =
element_blank(),
      panel.grid.minor = element_line(colour = "grey90"),
      panel.grid.major = element_line(colour = "grey90"),
      panel.grid.major.x = element_line(colour = "grey90"),
      title = element_text(size = 15),
      axis.text = element_text(size = 10),
      axis.title = element_text(size = 12, face = "bold")) +
      labs(x = "Time", y = "Load (kw)",
      title = paste("Forecast of MLR (", n_type[1], "); ", "week: ", i, ";
MAPE: ",
      round(lm_err_mape_1[i], 2), "%", sep = "")))
    ani.pause()
  }
}, movie.name = "industry_1.gif", ani.height = 450, ani.width = 750)
```