LOAD FORECASTING USING HOLT-WINTERS METHOD

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1. ABSTRACT

The global demand for energy is increasing daily due to the constant growing of the civilization with the expansion of energy infrastructure and the addition of new needs. This load increments added to fossil fuels crisis and the global economic crisis, arises the need to minimize both the electricity consumption and the economic expenditure [1][2].

The National Grids operates the transmission network that connects power stations to electricity consumers. Is also responsible for balancing the demand and supply system and ensuring that power stations will be able to provide electricity in case of an unanticipated increase in electricity [3].

As energy cannot be stored it must be generated according to demand, in order to avoid both the wastage of energy sources as the economic one. [4]

So, this is what this Thesis is about, study different algorithms capable of predicting load consumption.

2. INTRODUCTION

This technique can be carried out with different methods, which can be classified into two groups: primarily statistical techniques (such as regression models, exponential smoothing, and time series models), and artificial intelligence techniques (such as neural networks and support vector machines).

The different methods can also be classified according to their prediction, either short-term (a few hours), medium-term (a few weeks up to a year) or long-term (from one year to more). On long-term load forecasting is usually proposed an approach from one-year or more ahead, forecasting using daily peaks, whether on demand or weather; while in short-term it is usually used hourly peaks .

Load forecasting is then based on predicting values, but you must enter a series of values to obtain the results. Many of the more successful and common methods tend to include seasonal terms and/or trend in the model formulation. So, it is important to introduce as much DATA as possible. Most common used DATA are load values, as well as meteorological values, and there are also those that analyse holidays as well as days in which there may have been some social or natural disorder. As far as the outputs are concerned, the results tend to be applications of

probabilistic price forecasting, probabilistic transmission planning, and so forth. On long-term load forecasting is usually proposed an approach from one-year or more ahead, forecasting using daily peaks, whether on demand or weather [1], [5], [6].

3. METHODOLOGY OF HOLT-WINTERS

3.1 Single Exponential Smoothing

This is the simplest form of exponential smoothing and can be used only for fata without any systematic trend or seasonal components. Given such a time series, a sensible approach is to take a weighted average of past values.

So, for a series, $y_1, y_2, ..., y_n$, the estimate of the value *of y $_{n+1}$*, is:

$$\hat{y}_{n+1|n} = w_0 y_n + w_1 y_{n-1} + w_2 y_{n-2} + ...$$

or $\qquad \hat{y}_{n+1|n} = \sum_{i=0}^{\infty} w_i y_{n-i}$

Where w_i are the weights given to the past values of the series and sum to one. Since the most recent observations of the series are also the most relevant, it is logical that they should be given more weight at the expense of observations further in the past. This is achieved by assigning geometrically declining weights to the series. These decrease by a constant ratio and are of the form:

$$w_i = \alpha(1-\alpha)^i$$

Where i= 0, 1, 2, ... and α is the smoothing constant in the range $0 < \alpha < 1$.

3.2 Holt's method

This method works with the possibility of a series exhibiting some form of trend, whether constant or non-constant.

For a series $y1, y2, ..., yn$ the forecast function, which give an estimate of the series l steps ahead can be written as:

$$\hat{y}_{n+l|n} = m_n + lb_n \qquad\qquad l=1, 2, ...$$

where m_n is the current level and b_n is the current slope. The one step ahead is given by:

$$\hat{y}_{t/t-1} = m_{t-1} + b_{t-1}$$

We need now two separate smoothing constants, α_0 for the level and α_1 for the slope.

$$m_t = \alpha_0 y_t + (1-\alpha_0)(m_{t-1} + b_{t-1}) \qquad\qquad 0 < \alpha < 1$$

$$b_t = \alpha_1(m_t - m_{t-1}) + (1-\alpha_1)b_{t-1}$$

These equations can also be written in the appropriate error correction form:

$$m_t = m_{t-1} + b_{t-1} + \alpha_0 \varepsilon_t$$

$$b_t = b_{t-1} + \alpha_0 \alpha_1 \varepsilon_t$$

Holt's method requires starting values for m_t and b_t, to be inputted, and estimates of the values for α_0 and α_1 to be made. α can be estimated by minimizing the sum of squared errors. Also, it is often found that $m_1 = y$, and $b_1 = y_2 - y_1$ are reasonable starting values.

3.3 Holt- Winters Forecasting

This method is a good way to approach a product demand for a given period. Estimate that the demand is equal to, for example, the average of the historical consumption for a given period, giving a greater weight to the closest values in time. In addition, it takes into account the real forecast error in the following forecasts.

Holt-Winters is also called Triple Exponential Smoothing, the idea behind triple exponential smoothing is to apply three exponential smoothing, one to the seasonal components in addition to level and trend.

Terminology:

- Level: shows a weighted average of data.
- Trend: calculated by finding the ratio of the vertical change to the horizontal change between two distinct points on a line.

- Season: if a series appears to be repetitive at regular intervals, such an interval is referred to as a season.

Here we have three parameters that must be changed until the minimum SSE is achieved:

- α: smoothing factor/coefficient.
- β: smoothing trend factor/coefficient.
- γ: smoothing factor for the seasonal component.

The general forecast function for the multiplicative Holt-Winters method is:

$$\hat{y}_{n+l|n} = (m_n + lb_n)c_{n-s+l} \qquad\qquad l=1, 2, \ldots$$

Where m_n is the component of level, b_n is the component of the slope, and c_{n-s+1} is the relevant seasonal component, with s signifying the seasonal period (e.g. 4 for quarterly data and 12 for monthly data.)

If a monthly time series is considered, the one step ahead forecast is given by:

$$\hat{y}_{n+1|n} = (m_n + b_n)c_{n-11}$$

The updating formula for the three components will each require a smoothing constant. If once again α_0 is used as the parameter for the level and α_1 for the slope, and a third constant α_2, is added as the smoothing constant for the seasonal factor, the updating equations will be:

$$m_t = \alpha_0 \frac{y_t}{c_{t-s}} + (1-\alpha_0)(m_{t-1} + b_{t-1})$$

$$b_t = \alpha_1(m_t - m_{t-1}) + (1-\alpha_1)b_{t-1}$$

$$c_t = \alpha_2 \frac{y_t}{m_t} + (1-\alpha_2)c_{t-s}$$

In this case, α_0, α_1, and α_2 all lie between zero and one. If the aforementioned additive version of Holt-Winters was used, the seasonal factor is simply added as opposed to multiplied into the one step ahead forecast function, and the level and seasonal updating equations involve differences as opposed to ratios:

$$\hat{y}_{n+1|n} = m_n + b_n + c_{n-11}$$

$$m_t = \alpha_0(y_t - c_{t-s}) + (1 - \alpha_0)(m_{t-1} + b_{t-1})$$

$$c_t = \alpha_2(y_t - m_t) + (1 - \alpha_2)c_{t-s}$$

The slope, b_t, remains unchanged.

$$m_0 = \sum_{t=1}^{s} y_t / s$$

Where s is the number of seasons. The starting value for the slope component can be taken from the average difference per time period between the first and second year averages.

$$b_0 = \frac{\left\{\sum_{t=1}^{s} y_t / s\right\} - \left\{\sum_{t=s+1}^{2s} y_t / s\right\}}{s}$$

Finally, the seasonal index starting value can be calculated after allowing for a trend adjustment, as follows:

$$c_0 = \frac{\{y_k - (k-1)b_0/2\}}{m_0} \qquad \text{(multiplicative)}$$

$$c_0 = y_k - \{m_0 + (k-1)b_0/2\} \qquad \text{(additive)}$$

Where k= 1, 2, …, s. Obviously this will lead to s separate values for c_0, which is what is required to gain the initial seasonal pattern.

The smoothing parameters are often selected between 0,02 and 0,2. It is again possible to estimate them by minimizing the sum of the squared one-step-ahead errors, but there is no exclusive combination of α_0, α_1, and α_2 which will minimize the square errors for all t [6], [10].

4. APPLICATION OF THE METHOD

4.1 Parameters

As discussed in the previous section, this method has three parameters that regulate the results curve (α, β and γ).

4.2 Errors

To achieve accurate results, two simple error indicators typical in statistics are used: SSE and MSE.

SSE: or Sum of Squared Errors, is the sum of the squares of residuals (derivations predicted from actual empirical values of data). It is used as an optimality criterion in parameter selection and model selection. Always non-negative, and values closer to zero are better [7], [8].

This indicator is used to determinate α, β and γ by the fitting process, simply running the algorithm repeatedly and selecting the values that give you the smallest SSE, taking into account that alpha, beta and gamma must have values between 0 and 1. The equation used is as follows:

$$\text{SSE} = \sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2$$

Where Y_i is the ith value of the variable to be predicted and $\hat{Y}$ is the predicted value.

In the next section, we can find an example of how the results are altered by changing the parameters in the annual prediction.

MSE: or Mean Squared Error, measures the average of the squares of the errors between the estimator and what is estimated. Is a measure of the quality of an estimator, always non-negative, and values closer to zero are better [9].

This other indicator is used to compare between the methods studied in this thesis. The equation used is as follows:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} \left(Y_i - \hat{Y}_i\right)^2$$

Where Y_i is the ith value of the variable to be predicted and $\hat{Y}$ is the predicted value.

5. PREDICTIONS

5.1 Predicting a single day in January 2013

For the first scenario, the third Wednesday of the years 2010, 2011 and 2012 have been used as data to predict the second Wednesday of 2013 (9th January). These days have been chosen because they are a working day already away from the Christmas holidays.
So our samples size for this scenario is 3 days (13th January of 2010, 12th January 2011 and 11th January 2012).
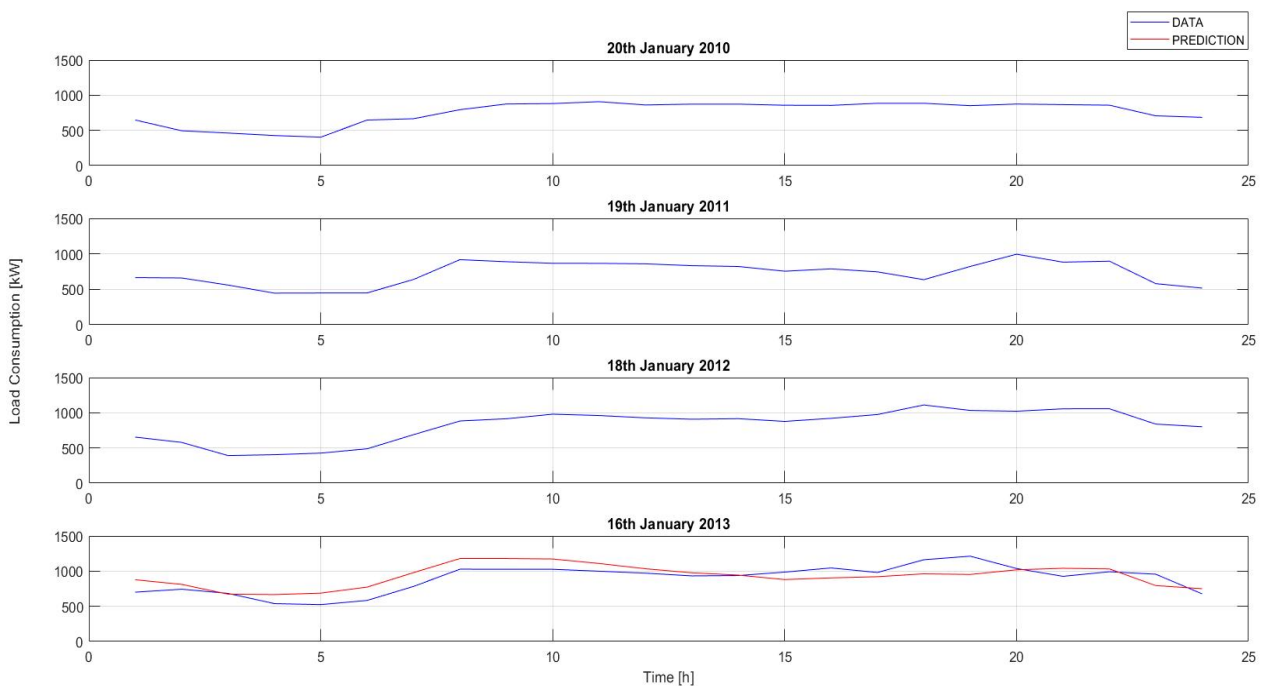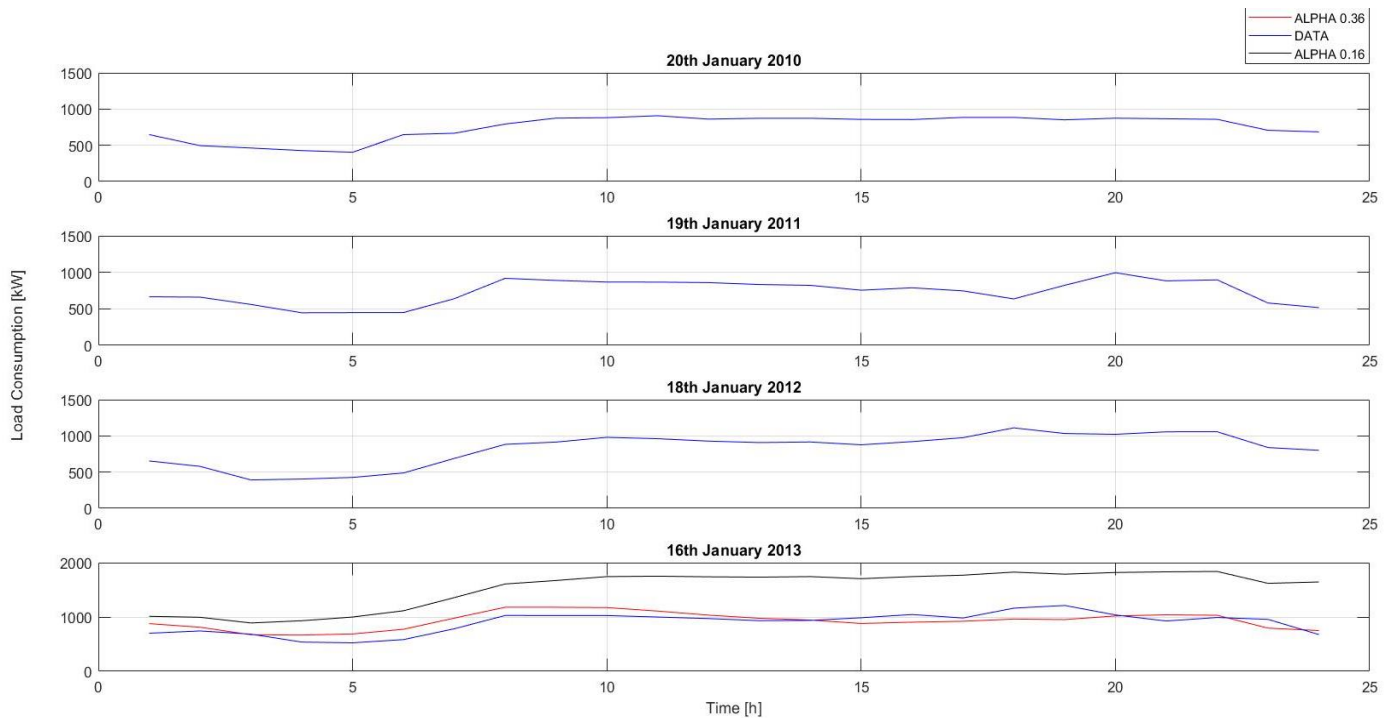

Graphic 1. Predicting a single day in January 2013 with DATA from January 2010, 2011 and 2012.

This graphic is done with a *SSE = 0,0283*. Its visible for the year 2013 that the prediction is not much accurate in the end. But is more accurate in the working hours because in the three data days we have a very similar behaviour. This is because the Holt-Winter's method is based on seasonality and tendency.

Other values calculated in this scenario:

- MSE = 0,0178.
- Alpha = 0,36.
- Beta = 0,34.
- Gamma = 0,78.

To see the importance of operating with the appropriate α, β and γ parameters, a new graphic is made in this scenario by changing α from 0,36 to 0,16.

Graphic 2. Predicting a single day in January 2013 with DATA from January 2010, 2011 and 2012 with two alphas.

The comparation is made in the last Subplot. In blue we have the Data, in red the best prediction with an alpha = 0,36, and the new one in black, with an alpha = 0,16.

We can see that with this new alpha the prediction is not as accurate as before. Here he have the errors in this new case:

- SSE = 0,0441.
- MSE = 0,4512.

Values which we cannot take as good due to its large size.

5.2 Predicting the 4ᵗʰ first weeks of 2013

This scenario takes the first 4 weeks of the years 2010, 2011 and 2012 to predict the first 4 weeks of 2013. Weeks are taken from Monday to Sunday.

So our samples size for this scenario is 4 weeks per 3 years, 12 weeks (from 4ᵗʰ January to 31ˢᵗ January 2010, from 3ʳᵈ January to 30ᵗʰ January 2011 and from 2ⁿᵈ January to 29ᵗʰ January 2012).
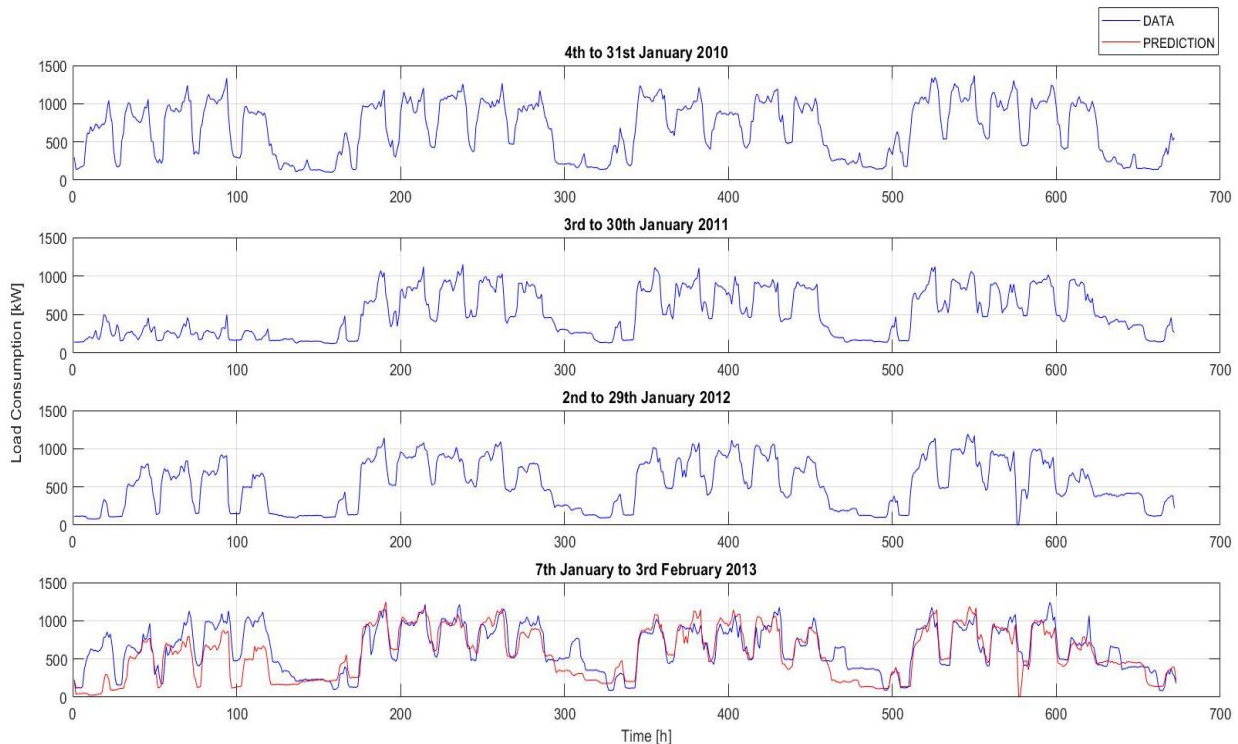
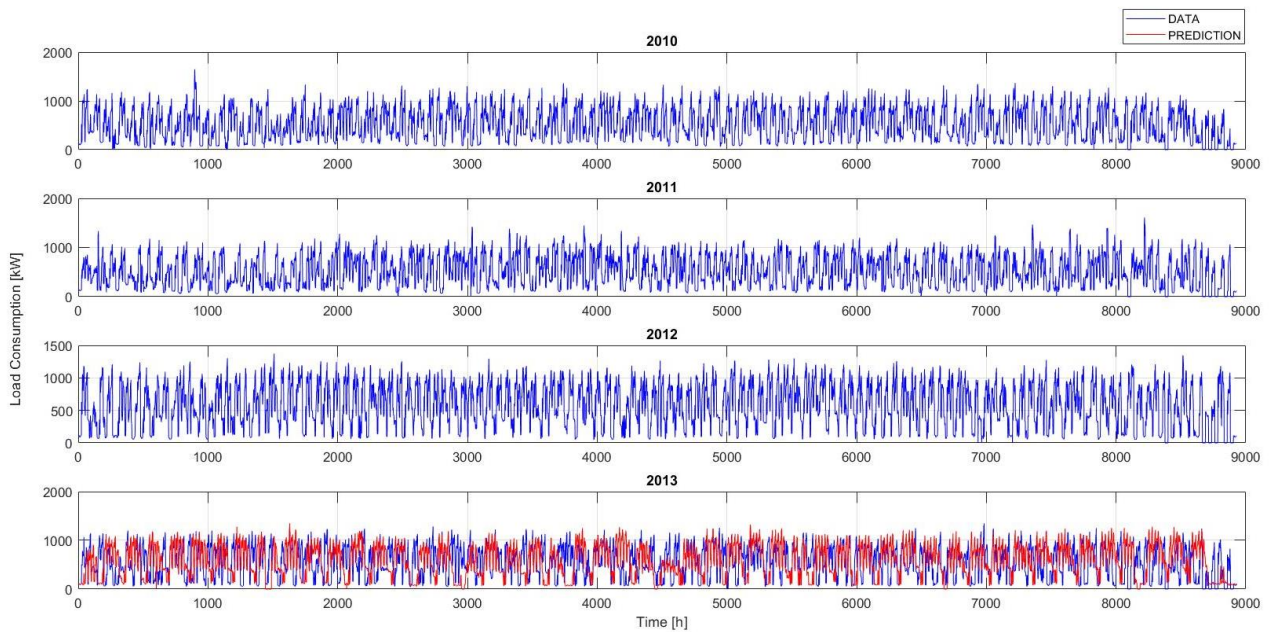**Graphic 3.** Predicting January 2013 with DATA from January 2010, 2011 and 2012.

This graphic is done with a *SSE = 0,0380*. In this case, the prediction is less accurate than before if we focus on the errors. As we have more points to study, the algorithm becomes more robust but the prediction less accurate. We can appreciate a tendency and a seasonality as well between weeks.

Other values calculated in this scenario:

- MSE = 0,0398.
- Alpha = 0,0125.
- Beta = 0,001.
- Gamma = 0,98.

5.3 Predicting 2013

Three years of data to predict January 2013. So our samples size for this scenario is from 1st January 2010 to 31st December 2012. In this case we have 26.784 data peaks.
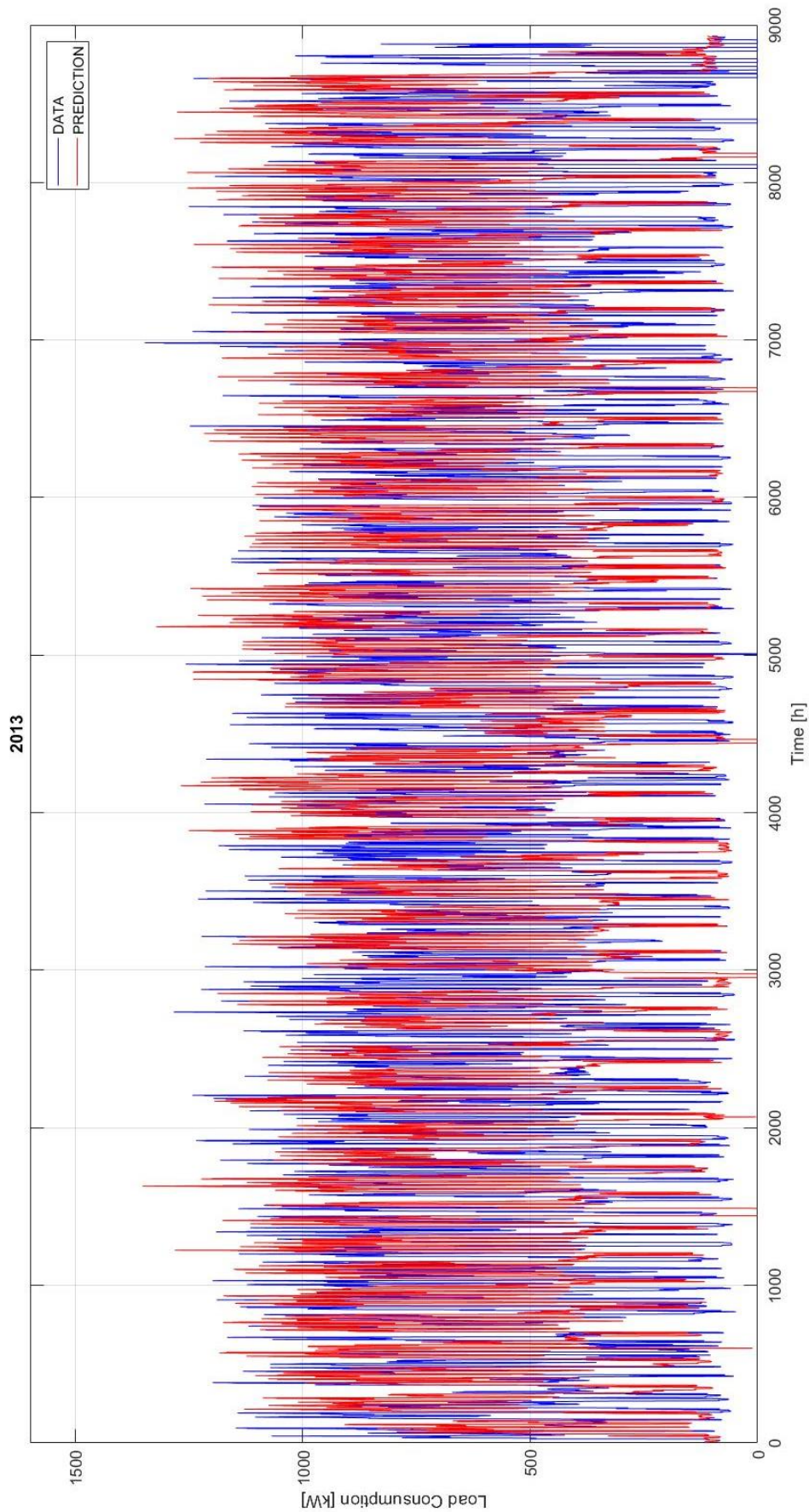

Graphic 4. Predicting January 2013 with DATA of the whole years 2010, 2011 and 2012.

This graphic is done with a *SSE = 1,8937*. This high SSE is because we have almost 30.000 points to study, so the error becomes much bigger.

Other values calculated in this scenario:

- MSE = 0,1769.
- Alpha = 0.
- Beta = 0,2.
- Gamma = 0,98.

In the next page, a zoom of this last prediction is made.

Graphic 5. Predicting January 2013 with DATA of the whole years 2010, 2011 and 2012.

6. COMPARING METHODS

This thesis studies a statistical algorithm capable of predicting values following the trends of a database, Holt-Winters. The results obtained by the method presented in this thesis have been compared with those ones obtained by the method discussed in the thesis [12].

In this section, both methods are compared with a third, which uses Artificial Neural Networks (ANN). Since most algorithms for data prediction use this type of model, it has been decided not to delve into it. The data have been entered in a free code to obtain results comparable to our study.

To compare the methods and see the accuracy of the results, three scenarios are presented. In each scenario, the real consumption values of 2013 are compared with those obtained in the predictions of each method.

The MSE (mean squared error) of the prediction is calculated as an indicator of the accuracy of the algorithm, and it will also be used to compare the methods.
The graphs are also used to visually compare the predictions with the actual load consumption values.

6.1 Prediction a single day in January 2013

For this prediction, three days of data are considered: 20th January 2010, 19th January 2011 and 18th January 2012 to predict 16th January 2013. These days are the third Wednesday of each year, chosen because in the first and second week of 2011 an unusual behaviour is seen and because Wednesday it is the middle day of the work week.
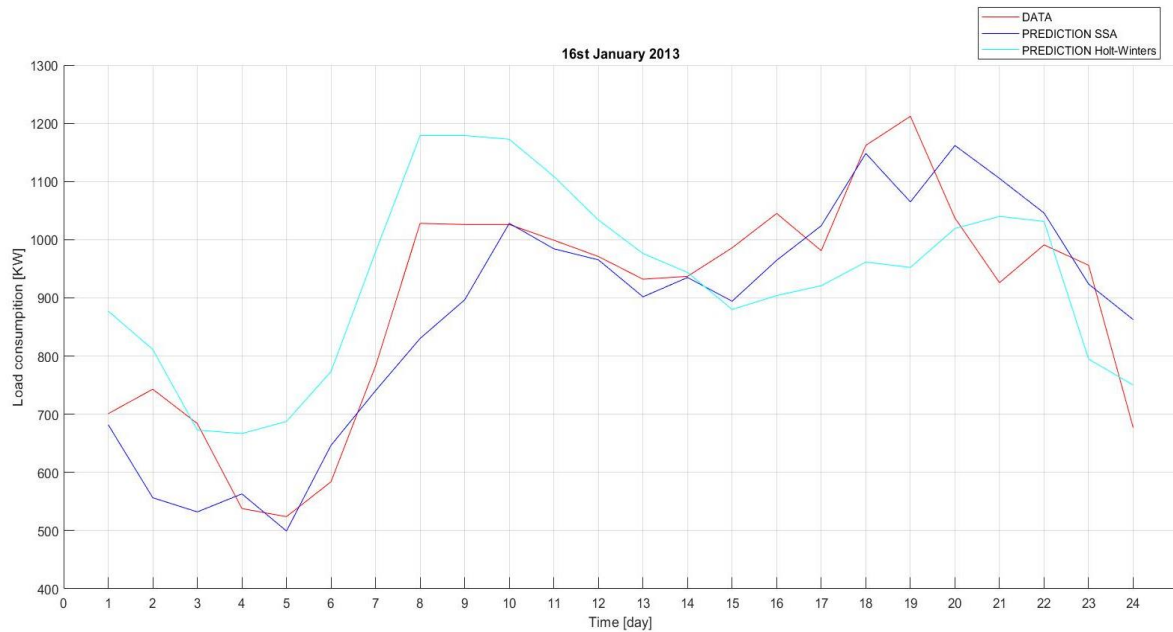
Graphic.6.-*Prediction of the load consumption 16st January 2013. (Source:MATLAB).*

The errors found in this prediction for Holt-Winters, SSA and ANN are similar. In this case, the least number of timesteps are predicted, only 24, except ANN, that predicts 22 timesteps due to the training parameter. The errors are of the same order (e^{-2}) which indicates that is a good prediction, since the error is considerably low.

In the SSA method the error is smaller, that means that it is more accurate than the Holt-Winters and ANN.
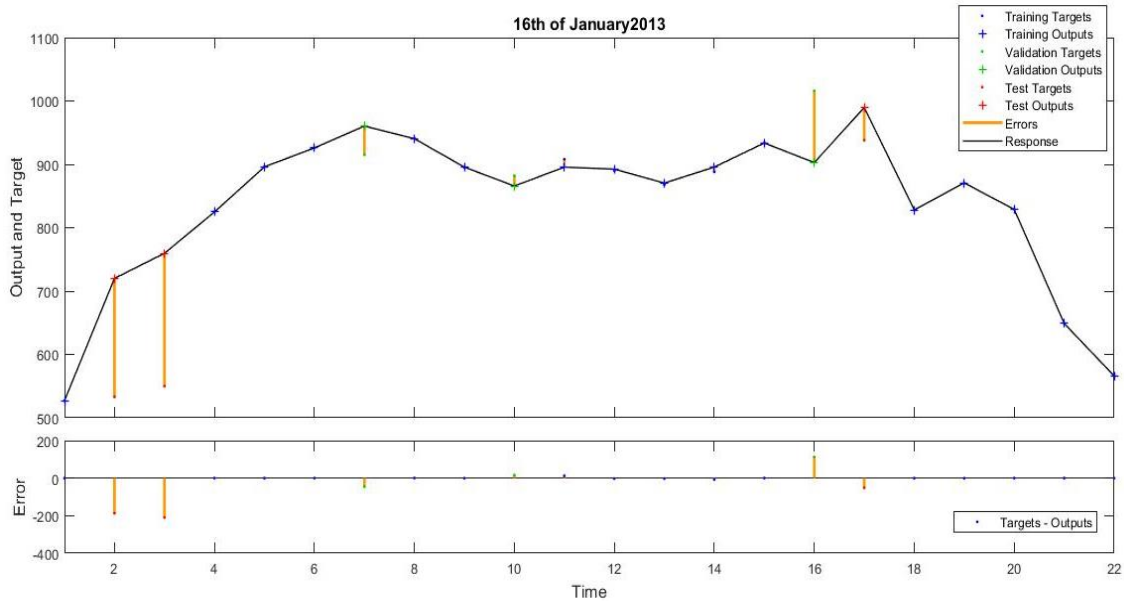
Graphic.7.-*Prediction of the load consumption 16st January 2013 with ANN. (Source:MATLAB).*

ERROR MSE		
Holt-Winters	**SSA**	**ANN**
0,0178	0,0103	0,0141

*Table.1.- MSE error in the prediction of 16th January 2013.*

6.2 Predicting the 4th first weeks of 2013

For this prediction, the hourly load data consumption considered is the 4 first weeks of the years 2010, 2011 and 2012, as described before.

In this case the error is quite similar to the scenario seen before (for the Holt-Winters and SSA), the order of magnitude of the error is the same. The error in ANN is much bigger than in the other methods. This method is more precise in the sections with less abrupt variations, but when peaks in the consumption are found, it is less accurate.

It is necessary to value that the number of predicted points is much bigger, 672 instead of 24.

In the SSA algorithm, error's order of magnitude is almost 1,5 times bigger than in the Holt-Winters. But it's still a good prediction, with an error considerably small.
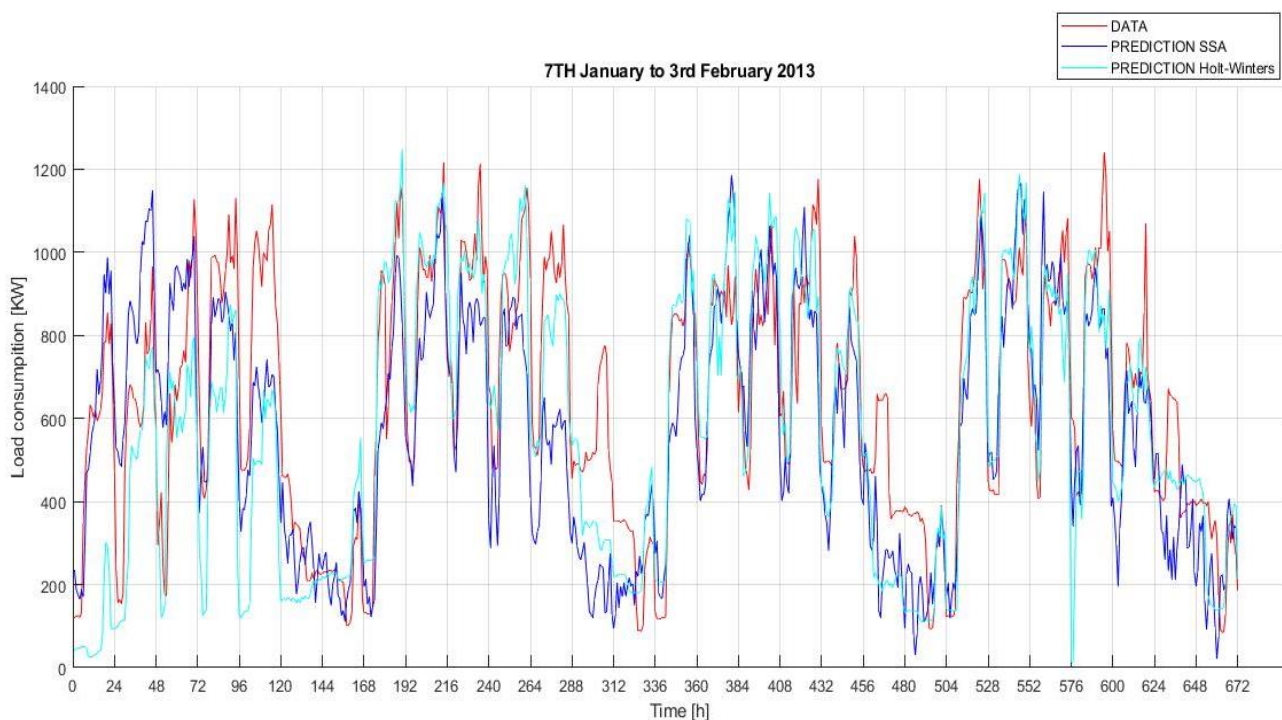
Graphic.8.-Prediction of the load consumption 7th January to 3rd February2013(Source:MATLAB).
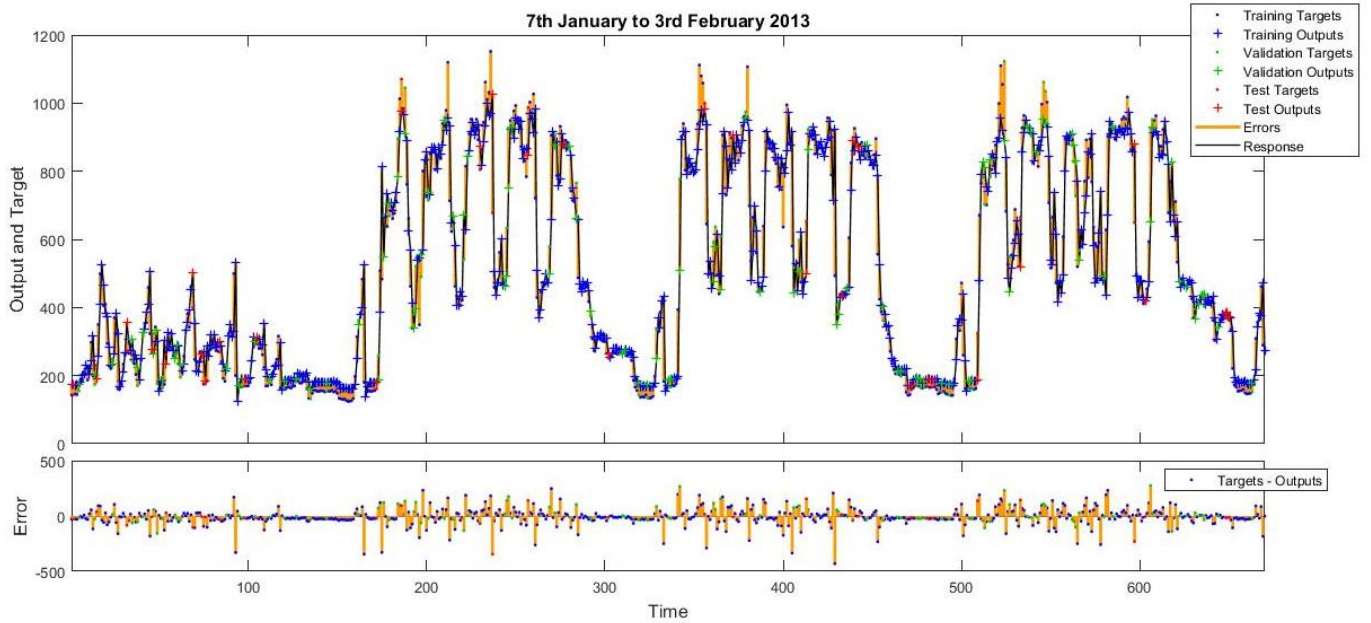
Graphic.9.-*Prediction of the load consumption 7ᵗʰ January to 3ʳᵈ February2013 using ANN (Source:MATLAB).*

ERROR MSE		
Holt-Winters	**SSA**	**ANN**
0,0398	0,0061	6,2563

***Table.2.-****MSE error in the prediction of the first 4 weeks 2013.*

6.3 Predicting 2013

For this forecast, the hourly load data consumption considered is the entire year, from 2010 to 2012.

In the SSA method and ANN, the prediction of a whole year is made with the daily average values of power consumption, because of the complexity of the algorithm, so the prediction vector has 365 peaks.

On the other hand, Holt-Winters prediction is made with 24 hours per day, so the prediction vector has 8.760 peaks.

But still this difference, both errors are comparable since the MSE is used. The SSA error is still smaller than the Holt-Winters. The error with ANN method is such bigger than the others.
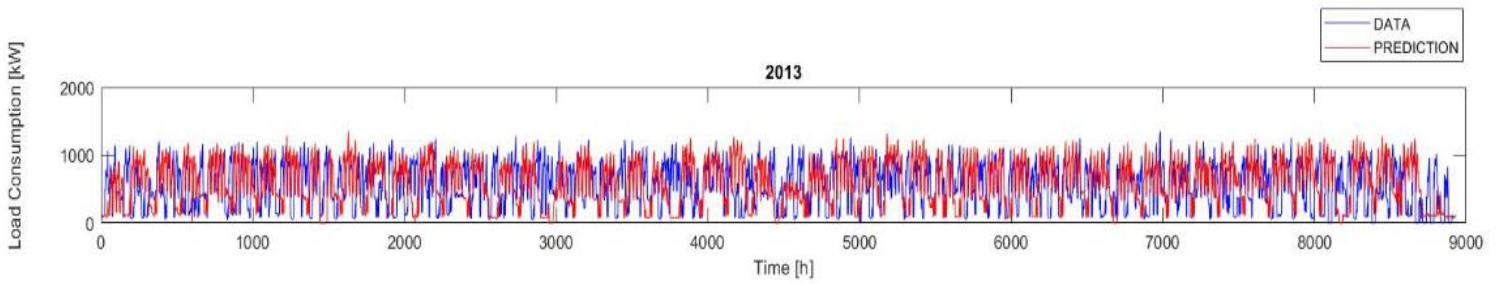
Graphic.10.-Prediction of the load consumption of 2013with Holt-Winters. (Source:MATLAB).
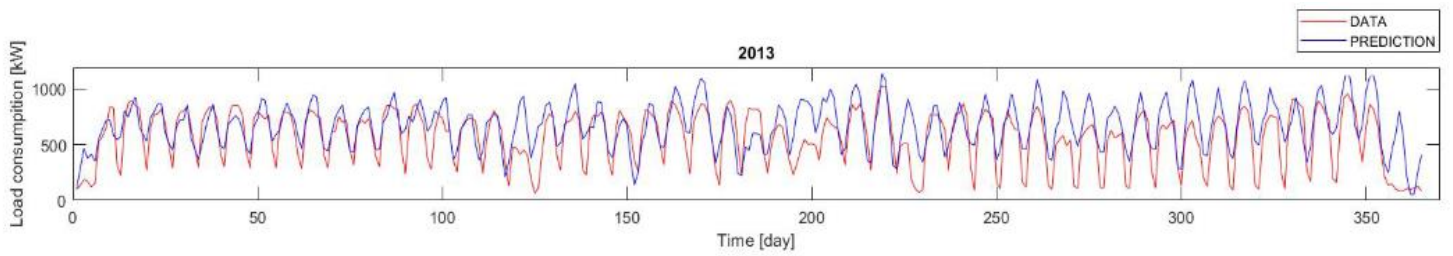
Graphic.11.-Prediction of the load consumption of 2013with SSA. (Source:MATLAB).
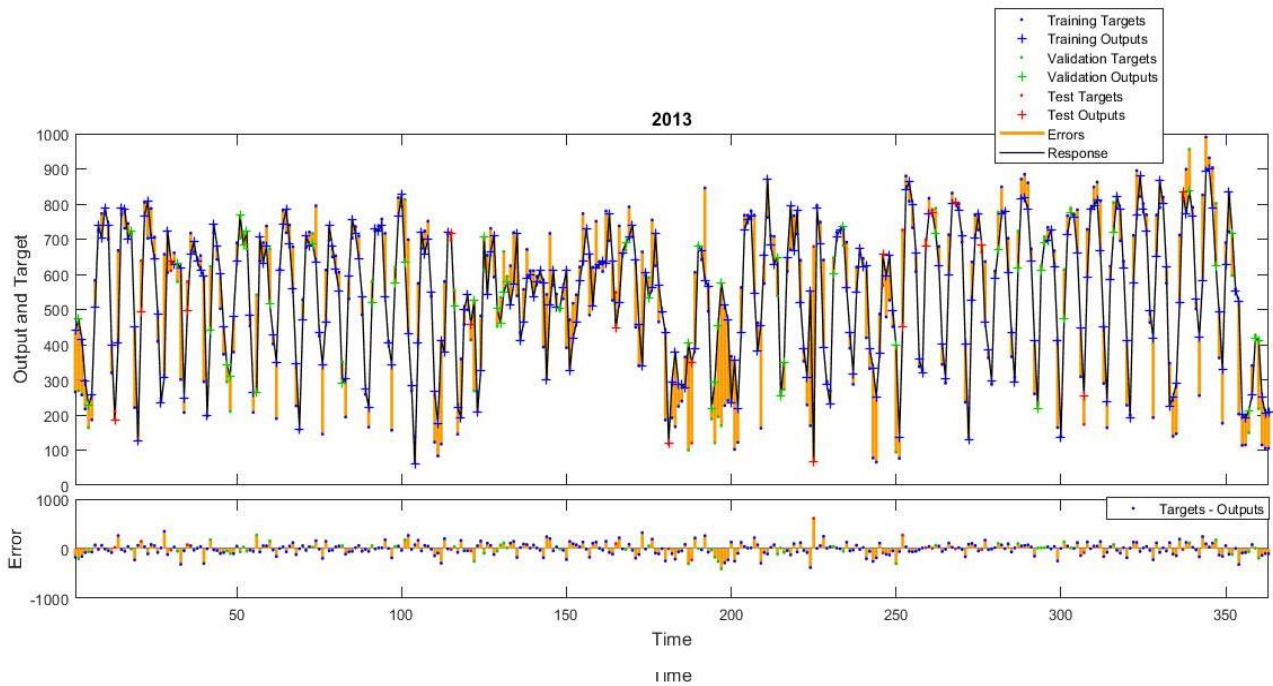
Graphic.12.-Prediction of the load consumption of 2013 using ANN. (Source:MATLAB).

ERROR MSE		
Holt-Winters	**SSA**	**ANN**
0,1944	0,0425	14,003

Table.3.-MSE error in the prediction of 2013.

Since there are so many points in the graph, a zoom has been made to get a better comparation between both methods.

There are now two more scenarios. The first zoom focuses on a part of the sample in which SSA produces a good prediction, from the 26th day of the year until de 46th, this is from 26th January (Saturday) till the 15th February (Friday).
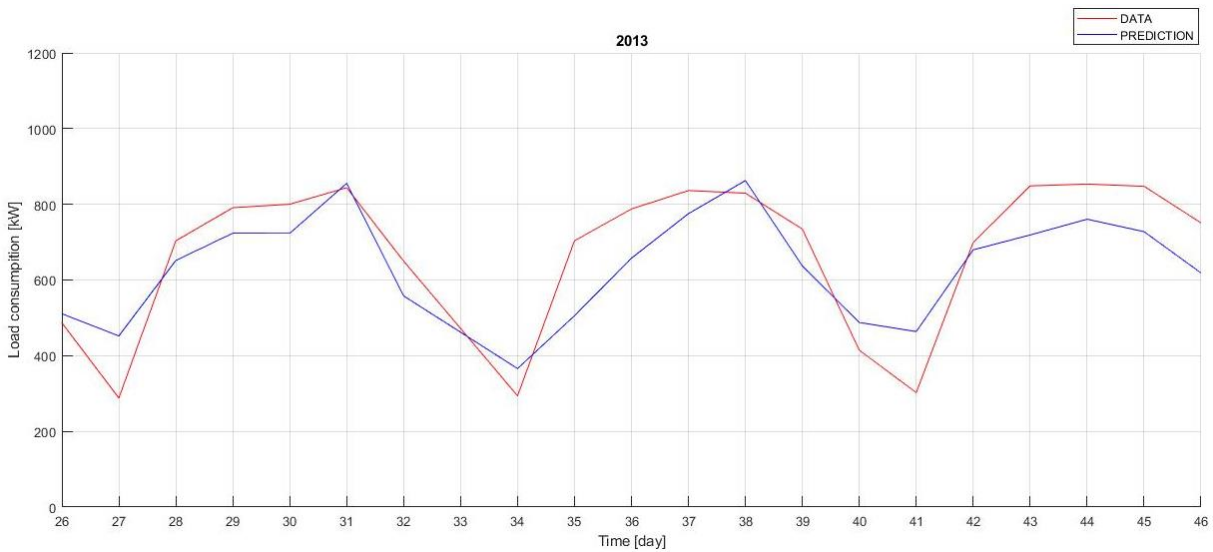
Same days are taken by Holt-Winters. It can be seen that the approximation is also good, considering that here are very low peaks in data, difficult to predict.

If we look at SSA, we will appreciate that there is trend every 7 days, being the day of the greatest consumption on January 31st 2010, which was Thursday.

Graphic.13.-*Zoom of Prediction of the load consumption of 2013with SSA. (Source:MATLAB).*
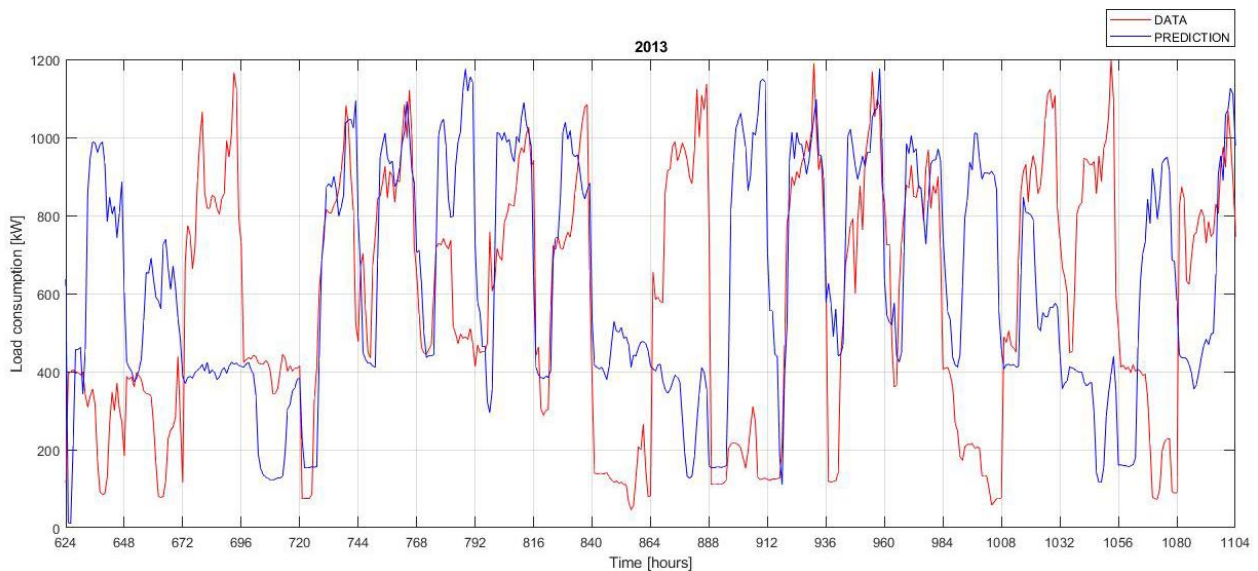
Graphic.14.-*Zoom of Prediction of the load consumption of 2013with Holt-Winters. (Source:MATLAB).*

The second zoom focuses on a part of the sample in which SSA produces a worst prediction than before, from the 185th day of the year until the 205th, this is from Thursday the 4th July till Wednesday the 24th July.
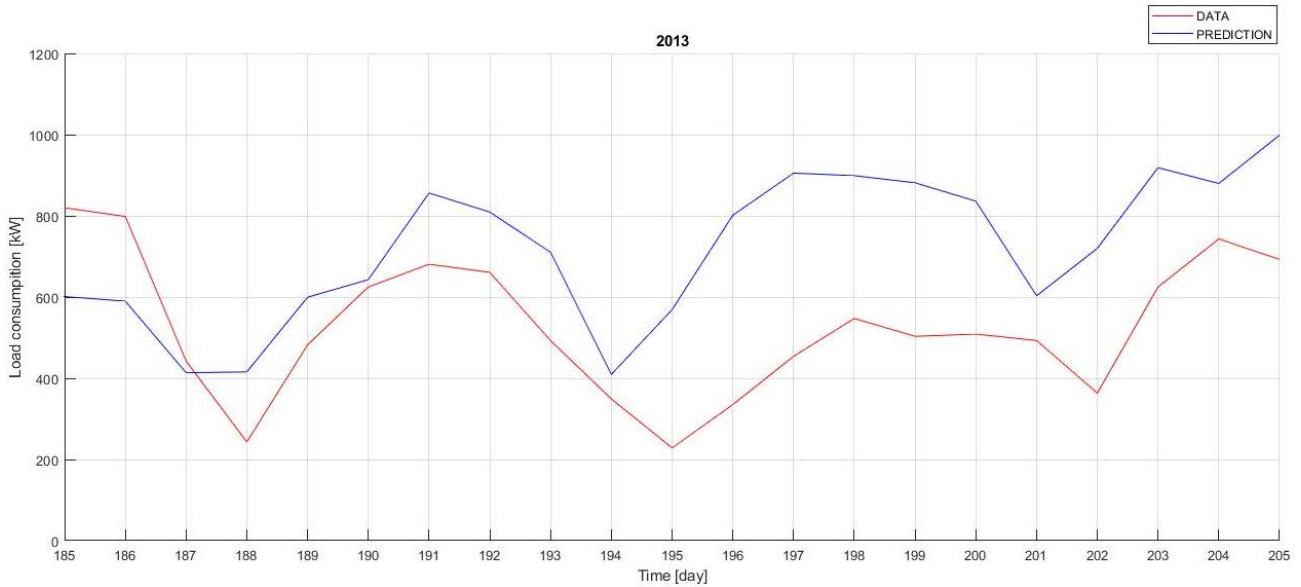

Graphic.15.-*Second Zoom of Prediction of the load consumption of 2013with SSA. (Source:MATLAB).*
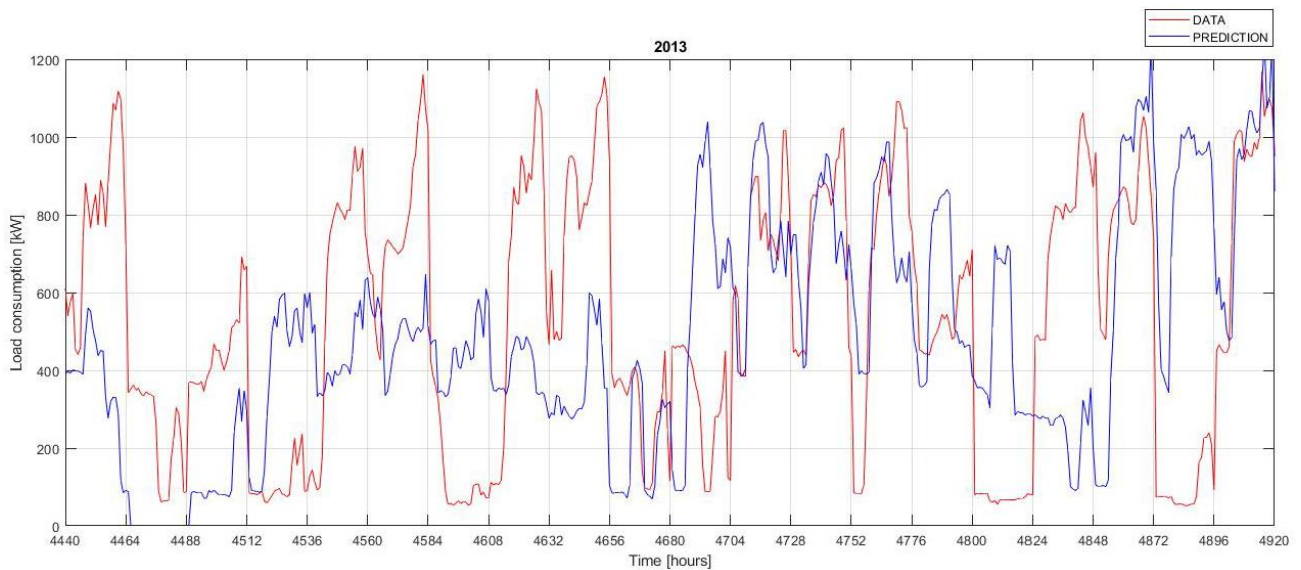
Graphic.16.-*Second Zoom of Prediction of the load consumption of 2013with Holt-Winters. (Source:MATLAB).*

7. CONCLUSIONS

Reading some load forecasting papers we saw that many technicians use Artificial Neural Networks. We realized that deepening this powerful method with our knowledge would take more time than we had. We decided to choose two known statistics methods, which still gave good results, to be compared later with a simple Neural Networks tool from Matlab. This tool has proven to be more difficult than we thought, and the results have not been as good as expected.

The simulation results indicate that the three algorithms have more accuracy with short-term forecasting (like most predictions seen in papers). As we have checked in the different predictions, SSA method is more accurate than Holt-Winters and ANN. The three methods, are more exactly in the first scenario, with less points to predict.
So we can say that the three methods are good for short-term forecasting.

One of the important points for having a good prediction, is the similarity of the data and the prediction, it means that is important to match the weeks (if the database starts in the 23rd week of the year, the prediction must start the 23rd as well). For this, both the data and the prediction must start on the same day of the week.

Both methods (Holt-Winters and SSA) are based on the seasonality of the data, so they can only be applied with data that follow a periodicity. This is why these scenarios have been chosen as they are presented.

So, we have worked with three methods on the same data, this has allowed us to have a deep vision of forecasting.

A possible extension of this project would be to deepen more with ANN and to introduce more data, such as meteorological, holidays…

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ANNEX

I.   INITIAL SEASONAL COMPONENTS

```matlab
function [init_comp] = initial_seasonal_components(observacions, season)
%INITIAL_SEASONAL_COMPONENTS
    switch season
        case 'd'
            slen = 24;
        case 'w'
            slen = 168;
        case 'm'
            slen = 744;
        case 'y'
            slen = 8928;
        case 's'
            slen = 672;
    end
    n_seasons = length(observacions)/slen;
    %Seasons averages
    for i = 1:n_seasons-1
        seasons_avg(i) = sum(observacions(slen*i:slen*i+slen))/slen;
    end

    %Seasonals
    for i = 1:slen
        sum_avg = 0.0;
        for j = 1:n_seasons-1
            sum_avg = sum_avg + observacions(slen*j+i)-seasons_avg(j);
        end
        seasonals(i) = sum_avg/n_seasons;
    end
    init_comp = seasonals;
end
```

II.   INITIAL TREND

```matlab
function [init_trend] = initial_trend(series, season)
%INITIAL_TREND
    switch season
        case 'd'
            slen = 24;
        case 'w'
            slen = 168;
        case 'm'
            slen = 744;
```

```matlab
      case 'y'
         slen = 8928;
      case 's'
         slen = 672;
   end
   init_trend = 0;
   for i = 1:slen
      init_trend = init_trend + (series(slen+i) - series(i))/slen;
   end
   init_trend = init_trend/slen;
end
```

III.   HOLTWINTERS

```matlab
function prediction = holtwinters(observacions, season, alpha, beta, gamma, type_pred, n_preds)

%   season = 'd','w','m','y','s'
   switch season
      case 'd'
         slen = 24;
      case 'w'
         slen = 168;
      case 'm'
         slen = 744;
      case 'y'
         slen = 8928;
      case 's'
         slen = 672;

   end

   switch type_pred
      case 'd'
         pred_len = 24;
      case 'w'
         pred_len = 168;
      case 'm'
         pred_len = 744;
      case 'y'
         pred_len = 8928;
      case 's'
         pred_len = 672;
   end

   pred_len = pred_len*n_preds;

   seasonals = initial_seasonal_components(observacions, season);

   for i = 1:length(observacions)+pred_len
      %cas inicial
      if (i == 1)
         smooth = observacions(1);
         trend = initial_trend(observacions, season);
         prediction(i) = observacions(i);
         continue
      end
      %prediction
      if (i >= length(observacions))
         m = i - length(observacions) + 1;
         prediction(i) = (smooth + m*trend) + seasonals(mod(i,slen)+1);

      %no prediction
```

```matlab
        else
            value = observacions(i);
            last_smooth = smooth;
            smooth = alpha*(value-seasonals(mod(i,slen)+1)) + (1-alpha)*(smooth+trend);
            trend = beta * (smooth-last_smooth) + (1-beta)*trend;
            seasonals(mod(i,slen)+1) = gamma*(value-smooth) + (1-gamma)*seasonals(mod(i,slen)+1);
            prediction(i) = smooth+trend+seasonals(mod(i,slen)+1);
        end
    end
end
```

IV. DAYS 1 DATA

```matlab
clear
HourlyConsumption = xlsread("data.xls");

%
cont = 1;

for j=17
    for i=1:24
        observacions(cont)=HourlyConsumption(i,j);
        cont=cont+1;
    end
end

for j=16
    for i=289:312
        observacions(cont)=HourlyConsumption(i,j);
        cont=cont+1;
    end
end

for j=15
    for i=577:600
        observacions(cont)=HourlyConsumption(i,j);
        cont=cont+1;
    end
end

figure(1)
plot(observacions)
```

V. DAYS 1 MAIN

```matlab
alpha = 0.65;
beta = 0.10;
gamma = 0.8;

%%

type_pred = 'd';
n_preds = 1;

result = holtwinters(observacions, 'd', alpha, beta, gamma,type_pred, n_preds);
```

```matlab
n=1;
for j=17
    for i=1:24
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

for j=16
    for i=289:312
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

for j=15
    for i=577:600
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

SSE=0;

for i=1:length(Y)
    SSE=SSE+(Y(i)-result(i))^2;
end
SSE

for j=20
    for i=865:888
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

MSE=0;

for i=73:96
    MSE=MSE+(Y(i)-result(i))^2;
end
MSE=MSE/24

%to kW
Y=Y*1000;
result=result*1000;
%

figure(3)
subplot(4,1,1);
plot(Y(1:24),'b')
grid on
title ('20th January 2010')
subplot(4,1,2);
plot(Y(25:48),'b')
grid on
title ('19th January 2011')
subplot(4,1,3);
plot(Y(49:72),'b')
grid on
title ('18th January 2012')
```

```matlab
subplot(4,1,4);
plot(Y(73:96),'b','displayname','DATA')
grid on
hold on
plot(result(73:96),'r','displayname','PREDICTION')
title ('16th January 2013')
xlabel ('Time [h]')
ylabel ('Load Consumption [kW]')
```

VI.   MONTH 2 DATA

```matlab
clear
HourlyConsumption = xlsread("data.xls");

%
cont = 1;

for j=8:35
    for i=1:24
        observacions(cont)=HourlyConsumption(i,j);
        cont=cont+1;
    end
end

for j=7:34
    for i=289:312
        observacions(cont)=HourlyConsumption(i,j);
        cont=cont+1;
    end
end

for j=6:33
    for i=577:600
        observacions(cont)=HourlyConsumption(i,j);
        cont=cont+1;
    end
end



figure(1)
plot(observacions)
```

VII.   MONTH 2 MAIN

```matlab
alpha = 0.0125;
beta = 0.001;
gamma = 0.98;

%%

type_pred = 'm';
n_preds = 1;

result = holtwinters(observacions, 's', alpha, beta, gamma,type_pred, n_preds);
```

```matlab
n=1;
for j=8:35
    for i=1:24
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

for j=7:34
    for i=289:312
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

for j=6:33
    for i=577:600
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

SSE=0;

for i=1:length(Y)
    SSE=SSE+(Y(i)-result(i))^2;
end
SSE

for j=11:35
    for i=865:888
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

for j=5:7
    for i=889:912
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

MSE=0;

for i=2016:2688
    MSE=MSE+(Y(i)-result(i))^2;
end
MSE=MSE/672

%to kW
Y=Y*1000;
result=result*1000;
%

figure(2)
subplot(4,1,1);
plot(Y(1:672),'b')
grid on
title ('4th to 31st January 2010')
subplot(4,1,2);
```

```
plot(Y(673:1344),'b')
grid on
title ('3rd to 30th January 2011')
subplot(4,1,3);
plot(Y(1345:2016),'b')
grid on
title ('2nd to 29th January 2012')
subplot(4,1,4);
plot(Y(2016:2688),'b','displayname','DATA')
grid on
hold on
plot(result(2016:2688),'r','displayname','PREDICTION')
title ('7th January to 3rd February 2013')
xlabel ('Time [h]')
ylabel ('Load Consumption [kW]')
```

VIII.   YEAR 3 DATA

```
clear
HourlyConsumption = xlsread("data.xls");

cont = 1;
for month = 0:35
    for j = 5:size(HourlyConsumption,2)
        for i = 1:24
            observacions(cont)=(HourlyConsumption(month*24 + i,j));
            cont = cont+1;
        end
    end
end
figure(1)
plot(observacions)
```

IX.   YEAR 3 MAIN

```
alpha = 0;
beta = 0.02;
gamma = 0.98;

%%

type_pred = 'y';
n_preds = 1;

result = holtwinters(observacions, 'y', alpha, beta, gamma,type_pred, n_preds);



n=1;
for j=5:35
    for i=1:288
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

for j=5:35
    for i=289:576
```

```matlab
            Y(n)=HourlyConsumption(i,j);
            n=n+1;
        end
end

for j=5:35
    for i=577:864
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

SSE=0;

for i=1:length(observacions)
    SSE=SSE+(observacions(i)-result(i))^2;
end
SSE

for j=5:35
    for i=865:1152
        Y(n)=HourlyConsumption(i,j);
        n=n+1;
    end
end

MSE=0;

for i=26785:35712
    MSE=MSE+(Y(i)-result(i))^2;
end
MSE=MSE/8928

%to kW
Y=Y*1000;
result=result*1000;
%
```

*This algorithm has been inspired by [11].