NRG4CAST

ENERGY FORECASTING

Evaluation and forecast of electricity consumption in tertiary sector building complex

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SEVENTH FRAMEWORK PROGRAMME

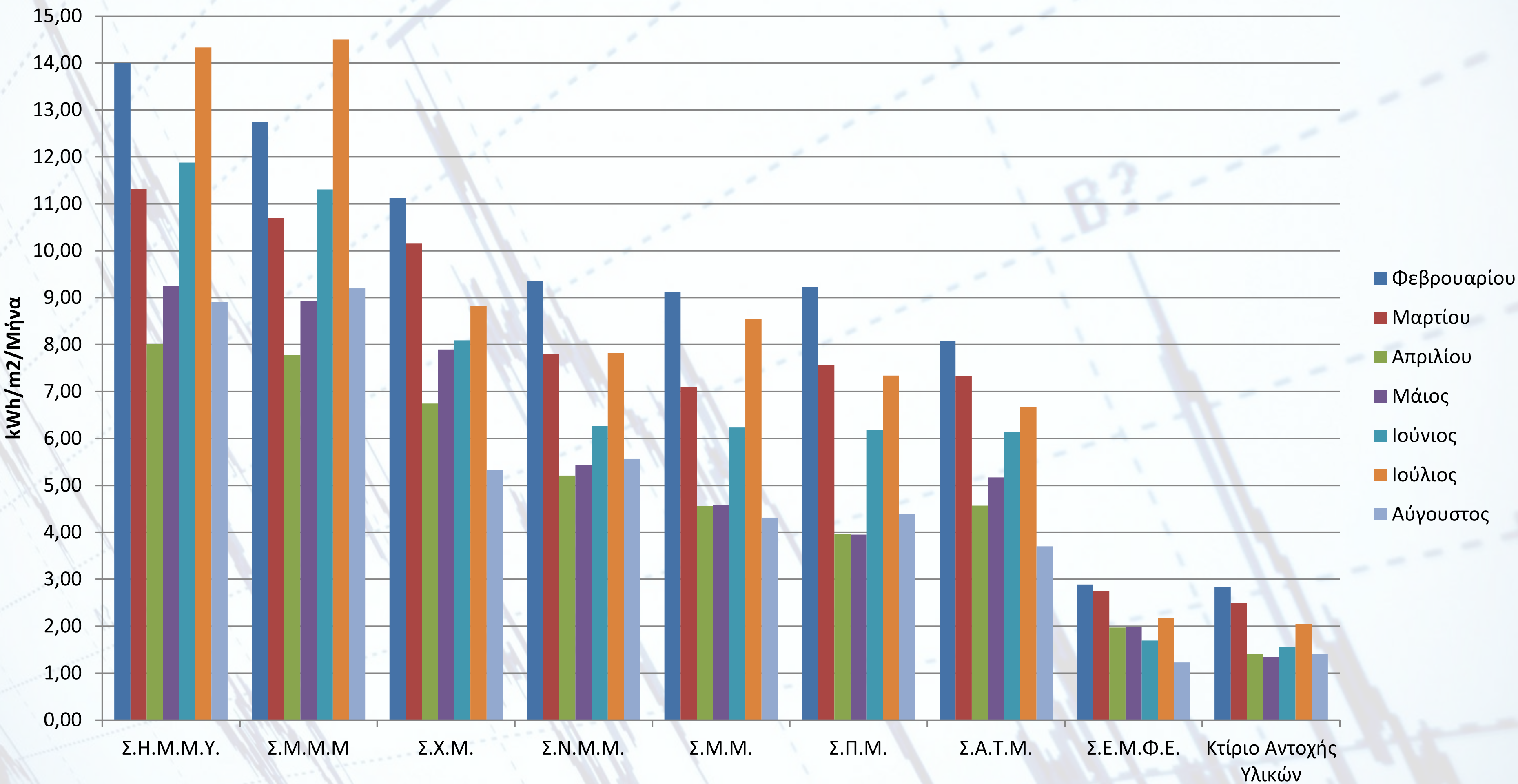
NTUA Campus

- School of Civil Engineer
- School of Mechanical Engineer
- School of Electrical and Computer Engineering
- School of Chemical Engineering
- School of Rural and Surveying Engineering
- School of Mining Engineering and Metallurgy
- School of Marine Engineering
- School of Applied Mathematical and Physical Science

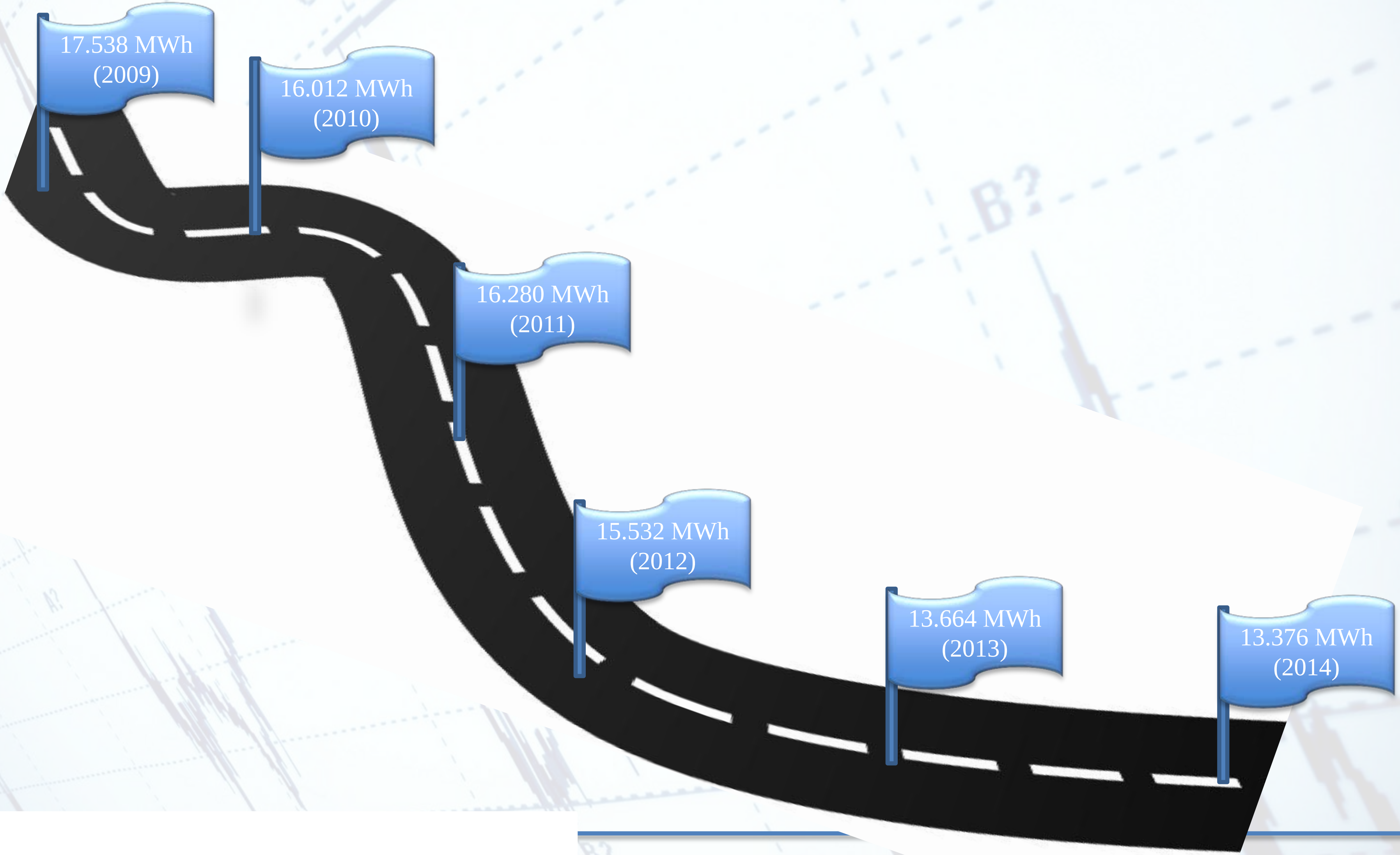
Annual energy needs are:

- Annual heating needs: 8100MWh
- Installed heating power: 25MW
- Installed cooling capacity: 14.5MW (70% due to heat pumps)
- Annual electricity needs are round 16000MWh and gradually decreasing

Monthly Measured Energy Consumption per m2 (kWh/m2/month)

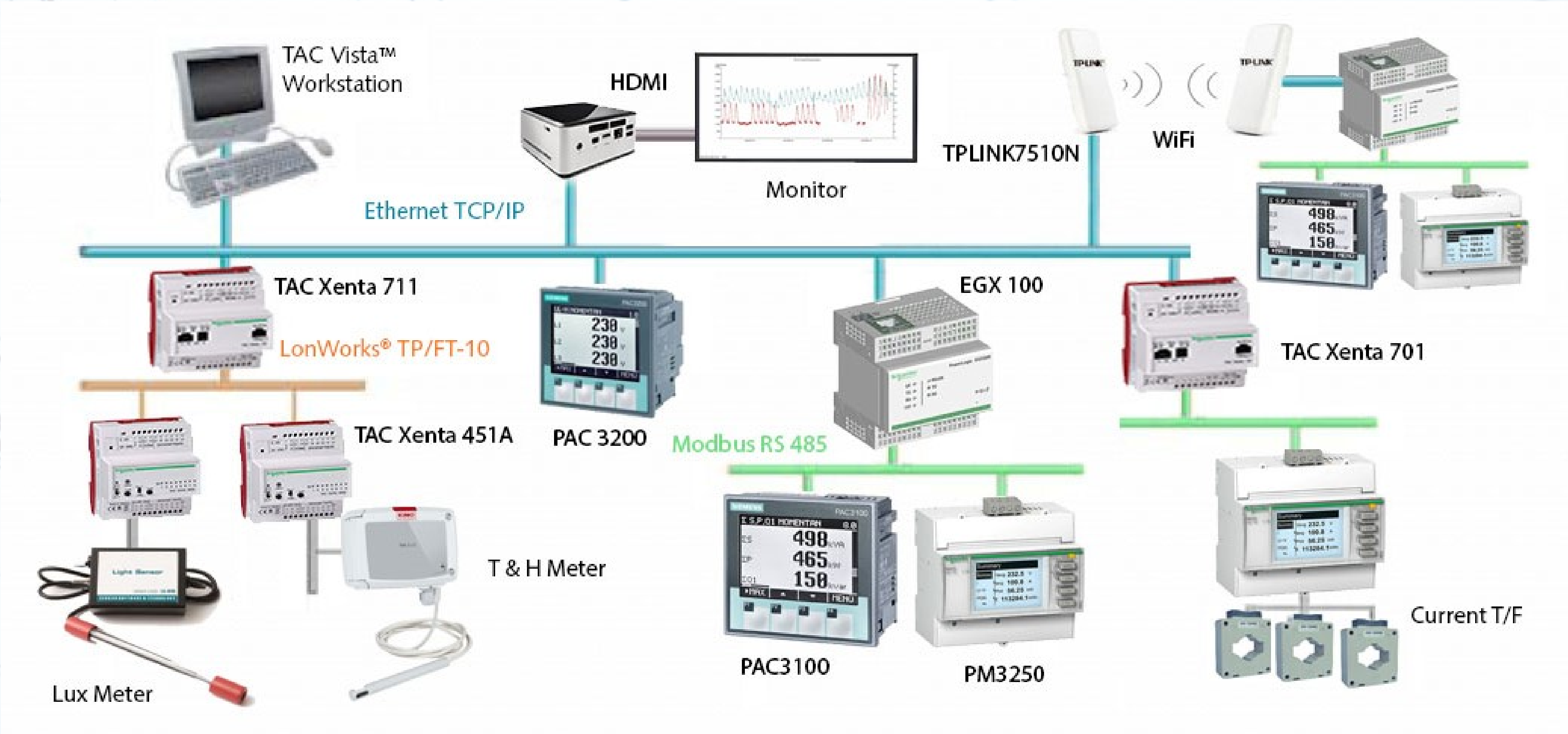


Annual Energy Consumption of the Campus

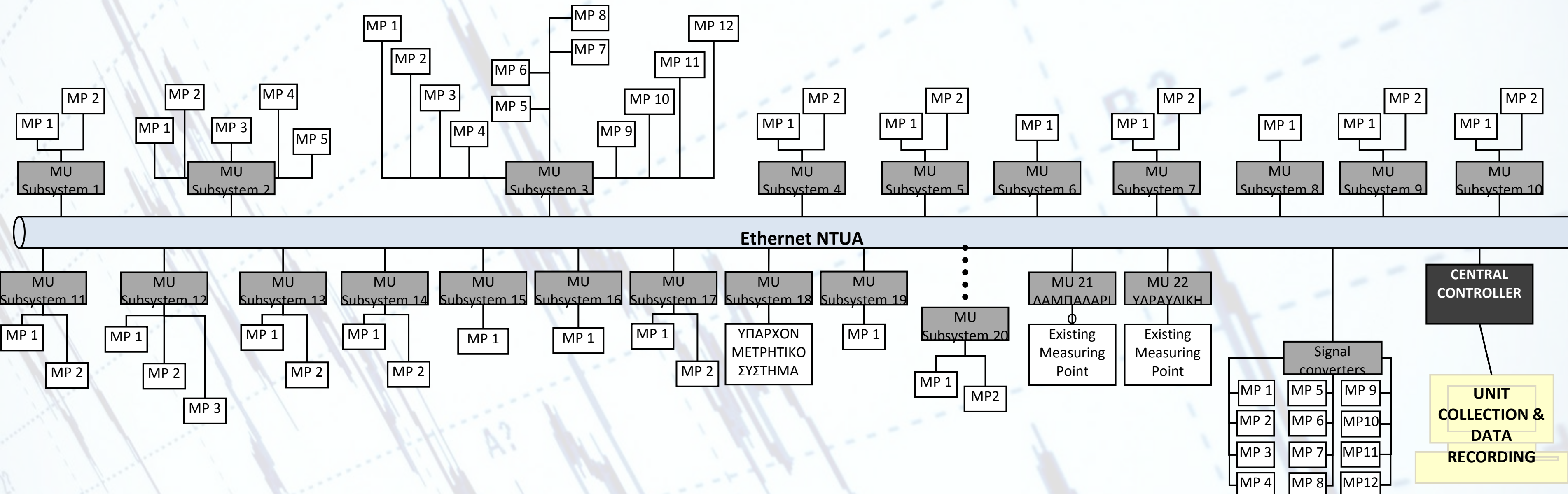


Measuring Devices

General Topology of the system



Topology



Explanations

MU: Monitoring Unit (PLC, communication element)

MP: Measuring Point

Wired connection

Wireless connection

Load Curves

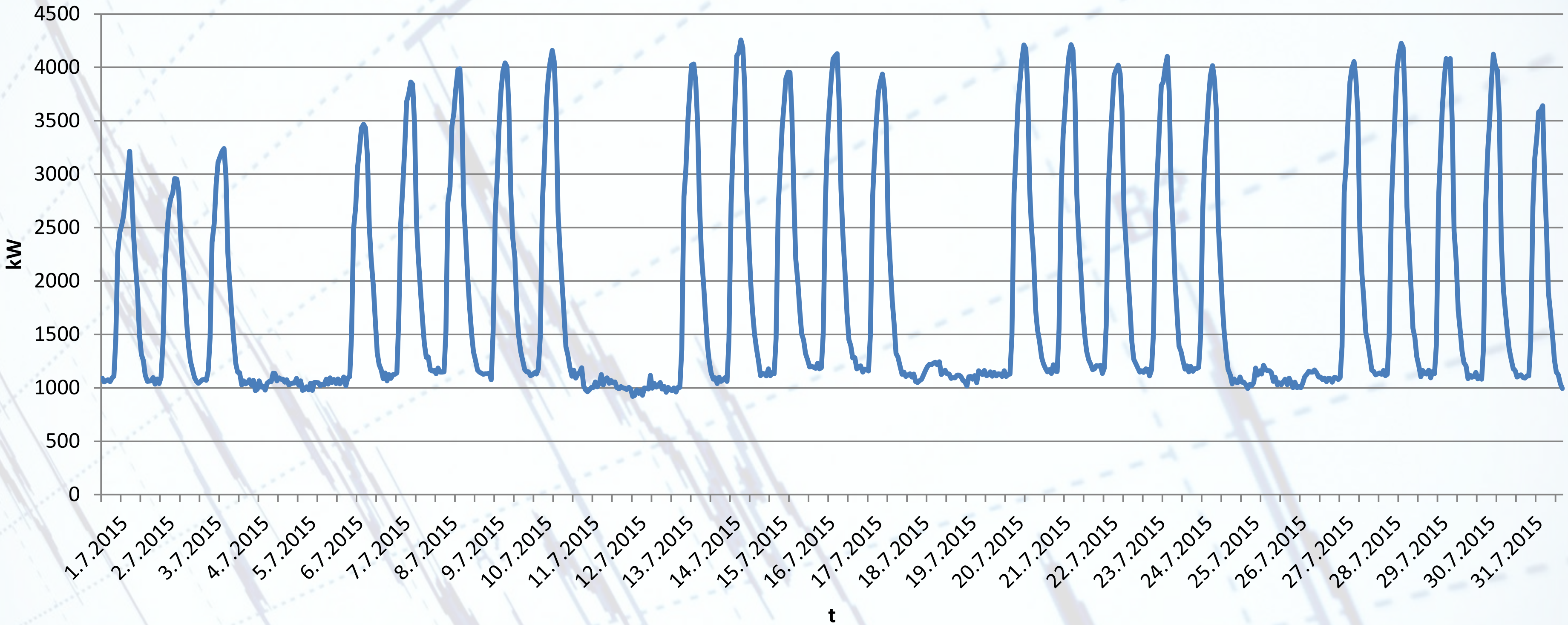
- **Chronological Load Curves**

The time load curve shows the variation of load with time. It shows the load demanded at any particular moment

- **Load Duration Curves**

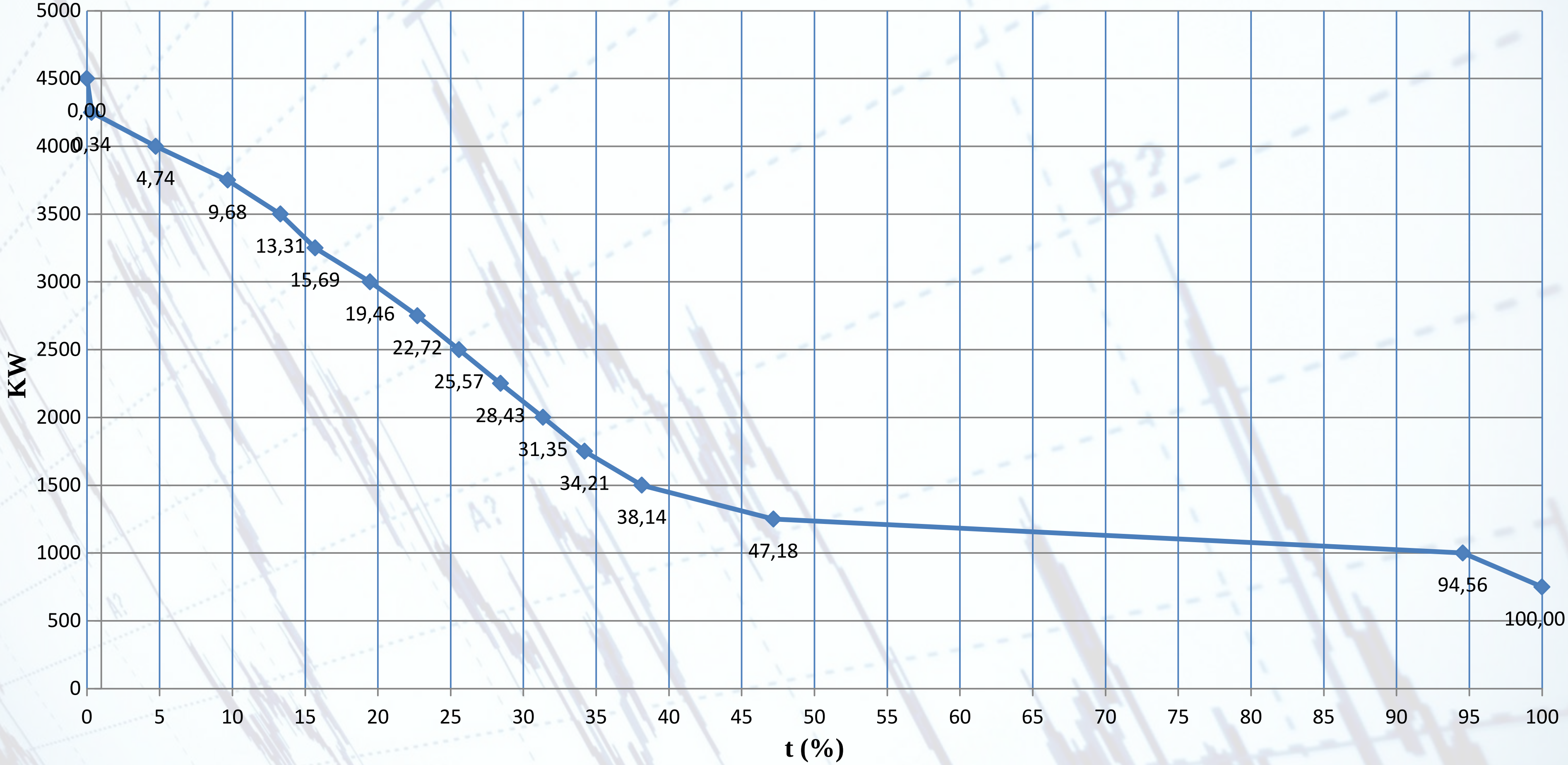
The load duration curve represents all the load elements with a descending order of magnitude starting from the left side with the maximum load and ending with the minimum load on the right, rather than using chronological order.

Chronological Load Curve



Characteristics of curve.		
Peak Load (P_A)	4,44	MW
Period (T)	744	h
Total Energy consumption (E)	1.348,86	MWh
Average Load (P_μ)	1,813	MW
Load factor (m)	0,41	

Load Duration Curve



Components of Time series

- **Time Series**

The time series is a collection of data recorded over a period of time – weekly, monthly or yearly: $Y_t = f(\mathrm{T}_t, S_t, C_t)$

Components:

- Trend components

A trend component exists when there is a long term increase or decrease in the data (T_t is the trend component at period t)

- Seasonality

A seasonality component exists when a series is influenced by seasonal factors (S_t is the seasonal component at period t)

- Cyclical component

A cyclical component exists when the data exhibit rises and falls that are not fixed period (C_t is the cyclical component at period t)

Data

- Electricity consumption in MW for the entire Campus, without extreme values

	Electricity consumption in MW of					
	2009	2010	2011	2012	2013	2014
Jan	1.680	1.728	1.608	1.568	1.416	1.262
Feb	1.440	1.284	1.424	1.300	1.272	1.201
Mar	1.494	1.188	1.520	1.456	1.176	1.184
Apr	1.092	1.158	1.184	1.016	1.064	968
May	1.548	1.368	1.168	1.152	1.040	1.030
Jun	1.920	1.638	1.320	1.496	1.352	1.272
Jul	1.560	1.528	1.704	1.736	1.536	1.405
Aug	1.446	1.512	1.152	1.112	1.032	937
Sep	1.356	1.384	1.312	1.272	1.124	1.170
Oct	1.350	1.296	1.128	1.152	1.016	1.066
Nov	1.368	1.168	1.416	1.080	1.037	1.050
Dec	1.284	1.243	1.344	1.192	1.240	1.215

Energy Demand Profile

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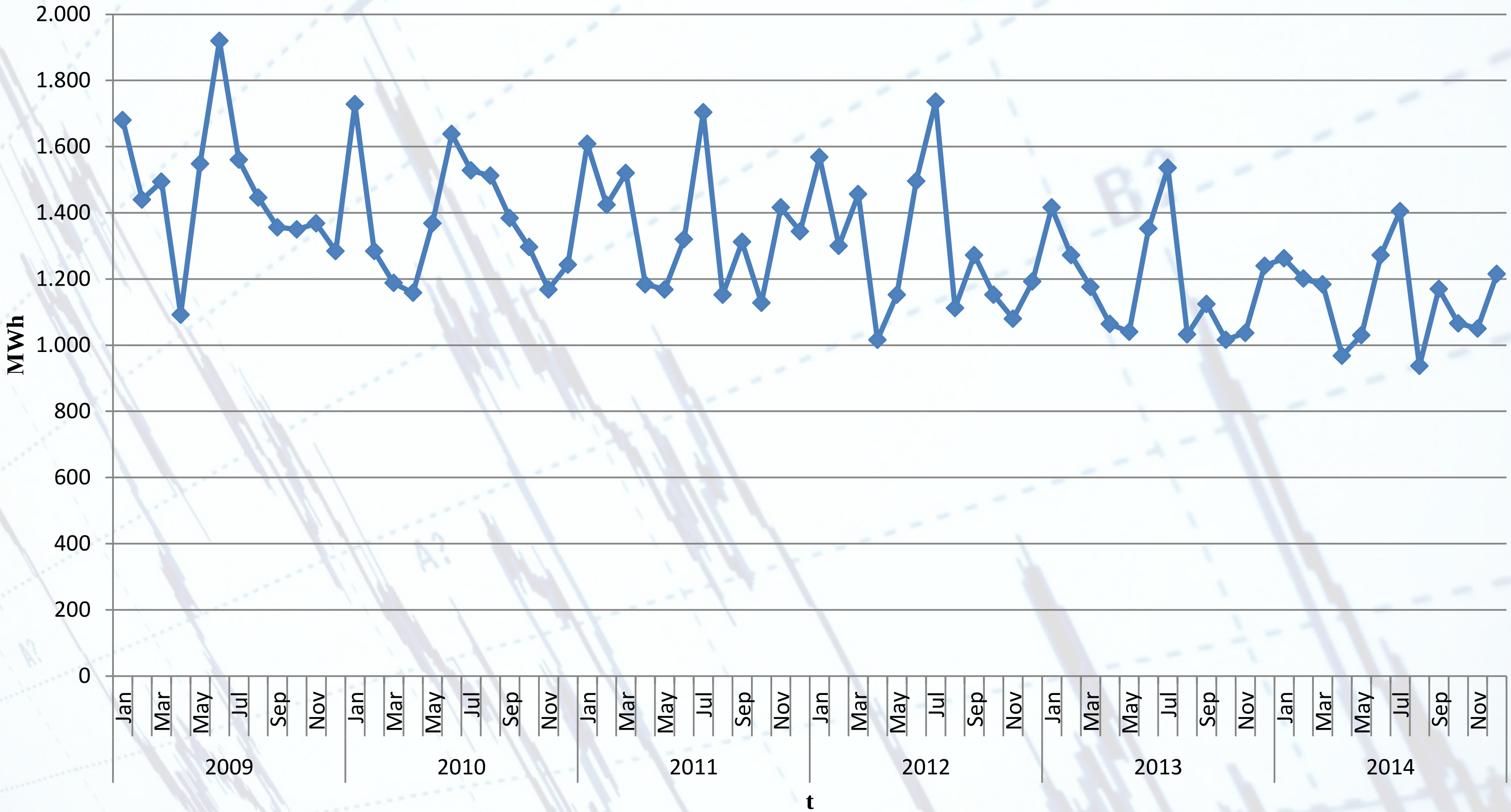


Forecasting Models

1. **Smoothing Methods:**

- Simple Moving Average
- Simple Exponential Smoothing
- Double Moving Average
- Holt Method, Exponential Smoothing Adjusted for trend
- Winters Method, Exponential Smoothing Adjusted for Trend and Seasonality

2. **Time Series Decomposition forecasting method**

Evaluation Criteria

- **MAD (Mean Absolute Deviation)**

$$MAD = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| = \frac{1}{n}\sum_{t=1}^{n}\left|e_t\right|$$

- **MSE (Mean Squared Error)**

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2 = \frac{1}{n}\sum_{t=1}^{n}e_t^2$$

- **RMSE (Root Mean Squared Error)**

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}e_t^2}$$

- **MAPE (Mean Absolute Percentage Error)**

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|Y_t - \hat{Y}_t\right|}{Y_t}\cdot 100\% = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|e_t\right|}{Y_t}\cdot 100\%$$

- **MPE (Mean Percentage Error)**

$$MPE = \frac{1}{n}\sum_{t=1}^{n}\frac{Y_t - \hat{Y}_t}{Y_t}\cdot 100\% = \frac{1}{n}\sum_{t=1}^{n}\frac{e_t}{Y_t}\cdot 100\%$$

Simple Moving Average

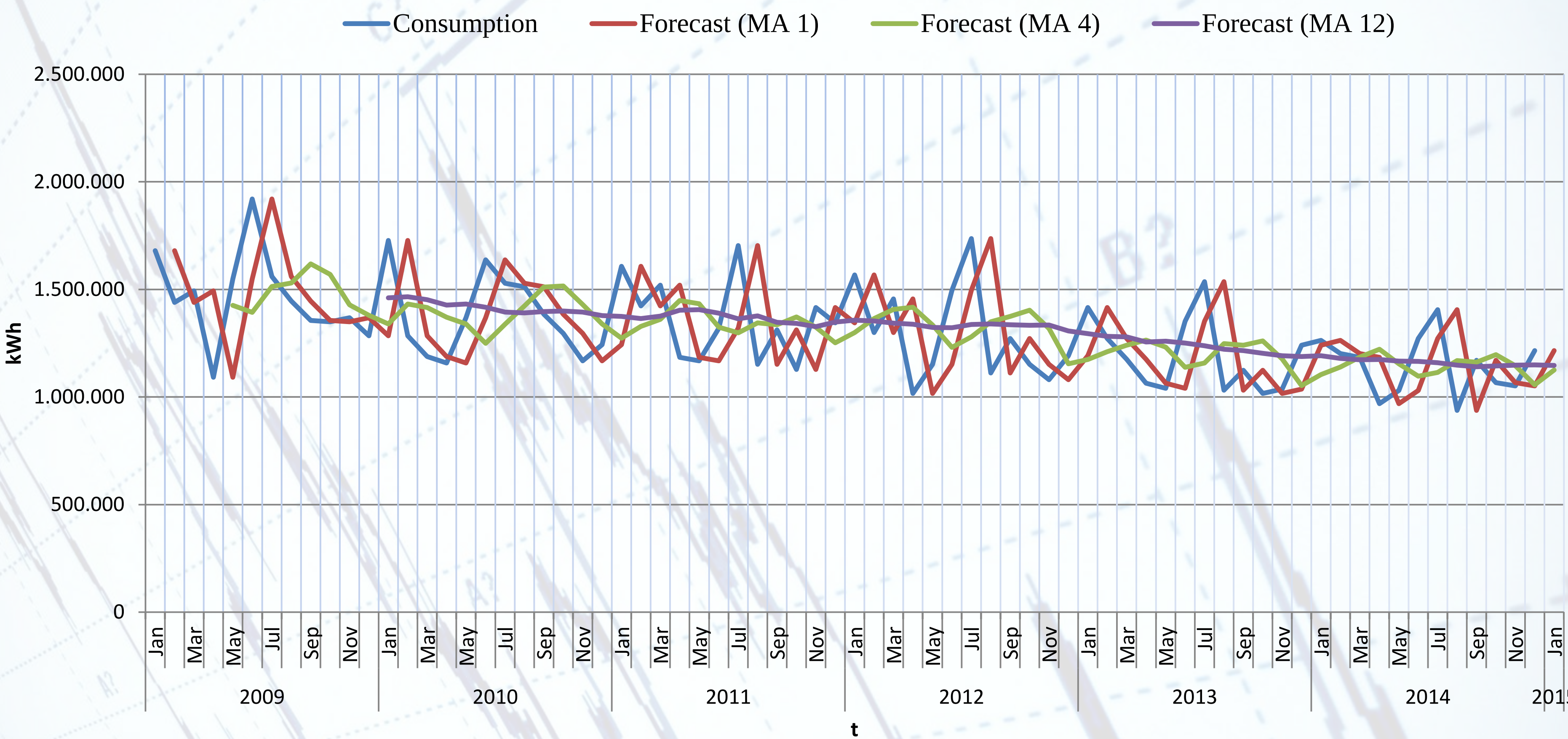
The formula for the Simple Moving Average is:

$$\hat{Y}_t = \frac{D_{t-1} + D_{t-2} + D_{t-3} + \ldots + D_{t-n}}{n}$$

General characteristics :

- The idea behind the moving averages is that observations which are nearby in time are also likely to be close in value
- Moving average of order n or MA(n) is when we use averages of n points
- Short-term averages respond quickly to changes in the value of the underlying, while long-term averages are slow to react
- Attaches equal importance to all values in the average
- Basic method

Simple Moving Average



Evaluation Criteria	MAD	MSE	RMSE	MAPE	MPE
Simple Moving Average (MA 1)	192732	58921804318	242738	15,01%	-2,17%
Simple Moving Average (MA 4)	183448	46809874469	216355	14,19%	-2,68%
Simple Moving Average (MA 12)	152644	31524619564	177551	12,24%	-4,31%

Simple Exponential Smoothing

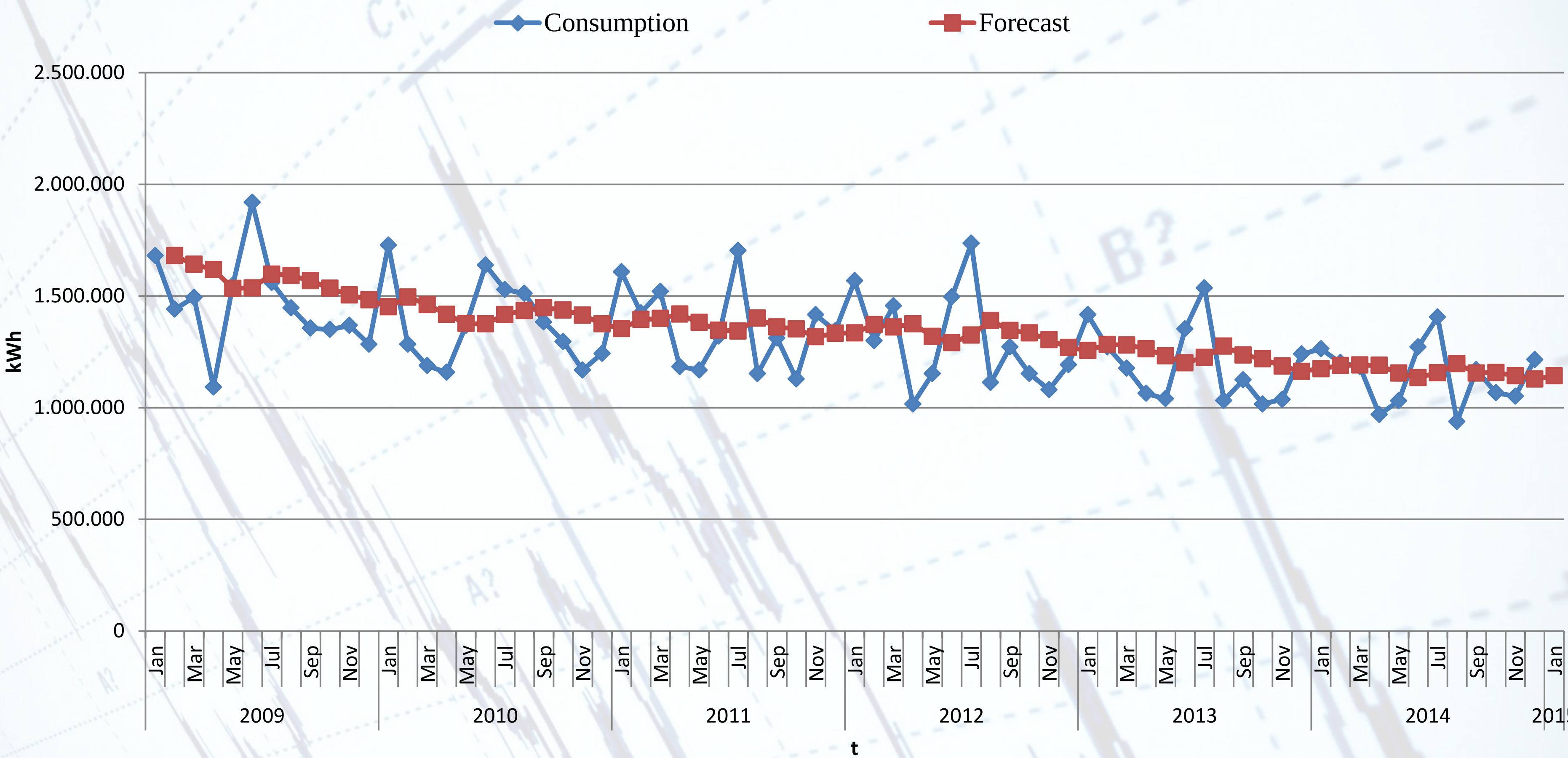
The basic equation for the Simple Moving Average is:

$$\hat{Y}_{t+1} = aY_t + (1-a)\hat{Y}_t, t > 0$$

General characteristics :

- The forecast is based <u>on weighting the most recent observation</u>
- The parameter, α, is called the <u>smoothing constant</u> and must be a value between 0 and 1
- Small data requirements
- We choose the best value for α so the value which results in the smallest MSE
- Is used when data pattern is approximately horizontal

Simple Exponential Smoothing



Evaluation Criteria	MAD	MSE	RMSE	MAPE	MPE
Simple Exponential Smoothing	166718	39166612709	197905	13,16%	-5,47%

Double Moving Average

The basic equations for the Double Moving Average is:

$$M_{t+1} = \frac{1}{m}\sum_{j=1}^{m} Y_{t-j+1} \qquad M'_{t+1} = \frac{1}{m}\sum_{j=1}^{m} M_{t-j+1}$$

$$a_t = 2M_t - M'_t$$

$$b_t = \frac{2}{m-1}(M_t - M'_t)$$

$$\hat{Y}_{t+h} = a_t + hb_t$$

General characteristics :

- Used when we have a linear trend in the data
- Reduce the amount of lag time found in traditional moving averages
- Small data requirements
- We choose the best value for m so the value which results in the smallest MSE
- Fast-acting moving average

Double Moving Average

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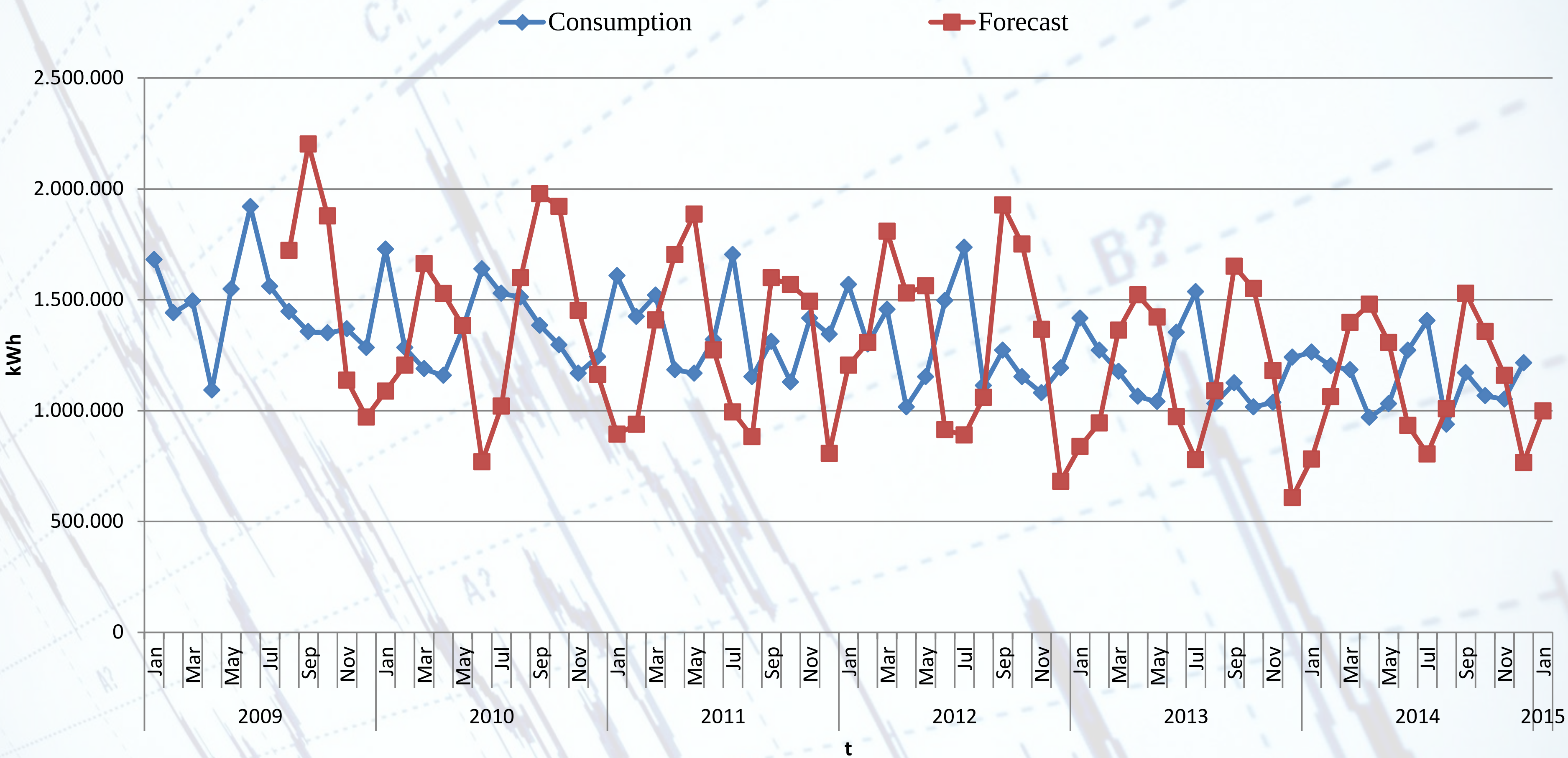

Evaluation Criteria	MAD	MSE	RMSE	MAPE	MPE
Double Moving Average	151861	32750974941	180972	11,89%	0,76%

Holt Method

The following equations are used when applying the Holt's method :

$$A_t = \alpha Y_t + (1-\alpha)(A_{t-1} + T_{t-1})$$

$$T_t = \beta(A_t - A_{t-1}) + (1-\beta)T_{t-1}$$

$$\hat{Y}_{t+h} = A_t + hT_t$$

General characteristics :

- In this method we smooth the <u>trend and the slope in the time series by using different constants for each</u>
- We choose the best value for α, β so the value which results in the smallest MSE
- Low values of α and β should be used when there are frequent random fluctuations in the data
- High values of α and β should be used when there is a pattern such as trend in the data

Holt Method

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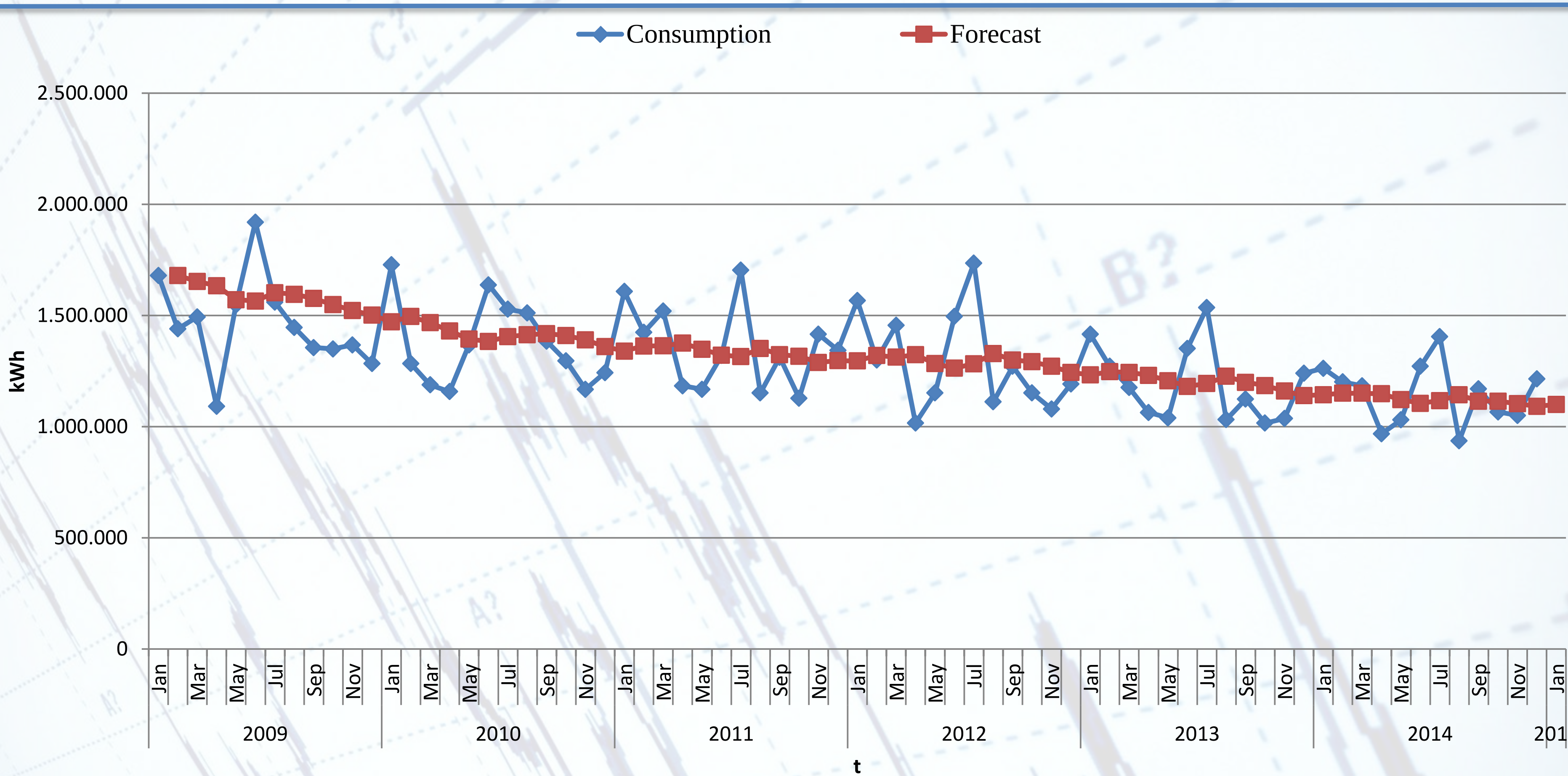


Evaluation Criteria	MAD	MSE	RMSE	MAPE	MPE
Holt Method	162375	37729697859	194241	12,60%	-3,54%

Winters Method

The Winters' model has the following components:

Smoothing value: $$A_t = \alpha \frac{Y_t}{S_{t-L}} + (1-a)(A_{t-1} + T_{t-1})$$

Trend estimate: $$T_t = \beta(A_t - A_{t-1}) + (1-\beta)T_{t-1}$$

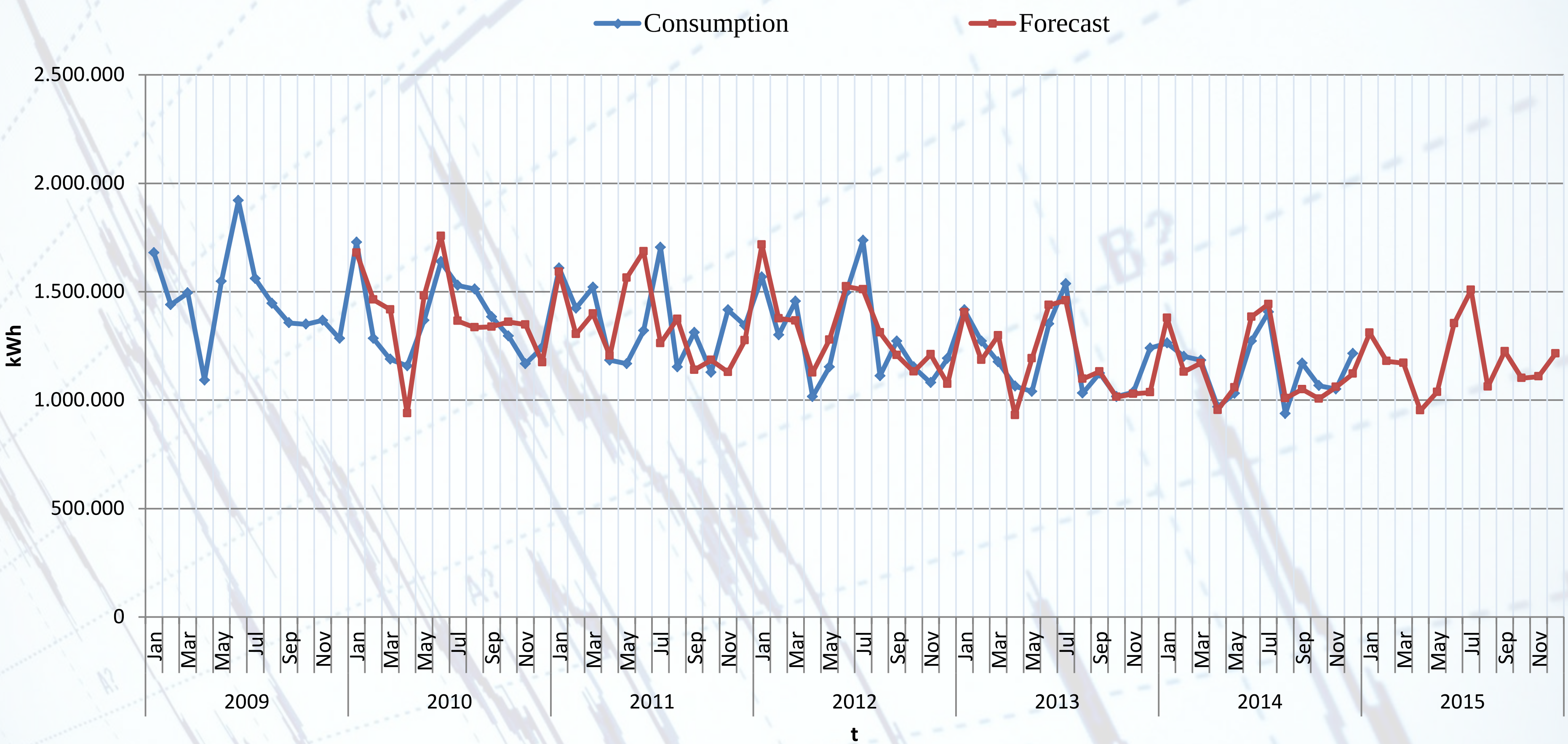
Seasonality estimate: $$S_t = \gamma \frac{Y_t}{A_t} + (1-\gamma)S_{t-L}$$

The forecast model is: $$\hat{Y}_{t+h} = (A_t + hT_t)S_{t+h-L}$$

General characteristics :

- Allows both trend and seasonal patterns to be taken into account
- This is an extension of the Holt's method of smoothing
- We choose the best value for α, β,γ so the value to be resulted in the smallest MSE

Winters Method



Evaluation Criteria	MAD	MSE	RMSE	MAPE	MPE
Winters Method	115656	22138504838	148790	9,03%	-0,84%

Time Series Decomposition

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Mathematical representation of the decomposition approach is :

$$\hat{Y}_{t+h} = T_{t+h} x S_{t+h} x C_{t+h}$$

- T_{t+h} is the trend component at future period t+h $T_{t+h} = a + b(t+h)$
- S_{t+h} is the seasonal component at future period t+h $S_{t+h} = SF_i$
- C_{t+h} is the cyclical component at future period t+h $C_{t+h} = CF_i$

General characteristics :

- We assume the time series is multiplicative
- The trend T_{t+h} is computed using a centered moving average. This removes the short-term fluctuations from the data so that the longer-term trend components can be more clearly identified
- The method of least squares can be used to estimate α and b
- The centered moving averages represent the deseasonalized data
- The degree of seasonality, called seasonal factor (SF), is the ratio of the actual value to the deseasonalized value
- The cyclical component of a time series is measured by a cycle factor (CF), which is the ratio of the centered moving average (CMA) to the Centered moving average trend (CMAT)

Time Series Decomposition

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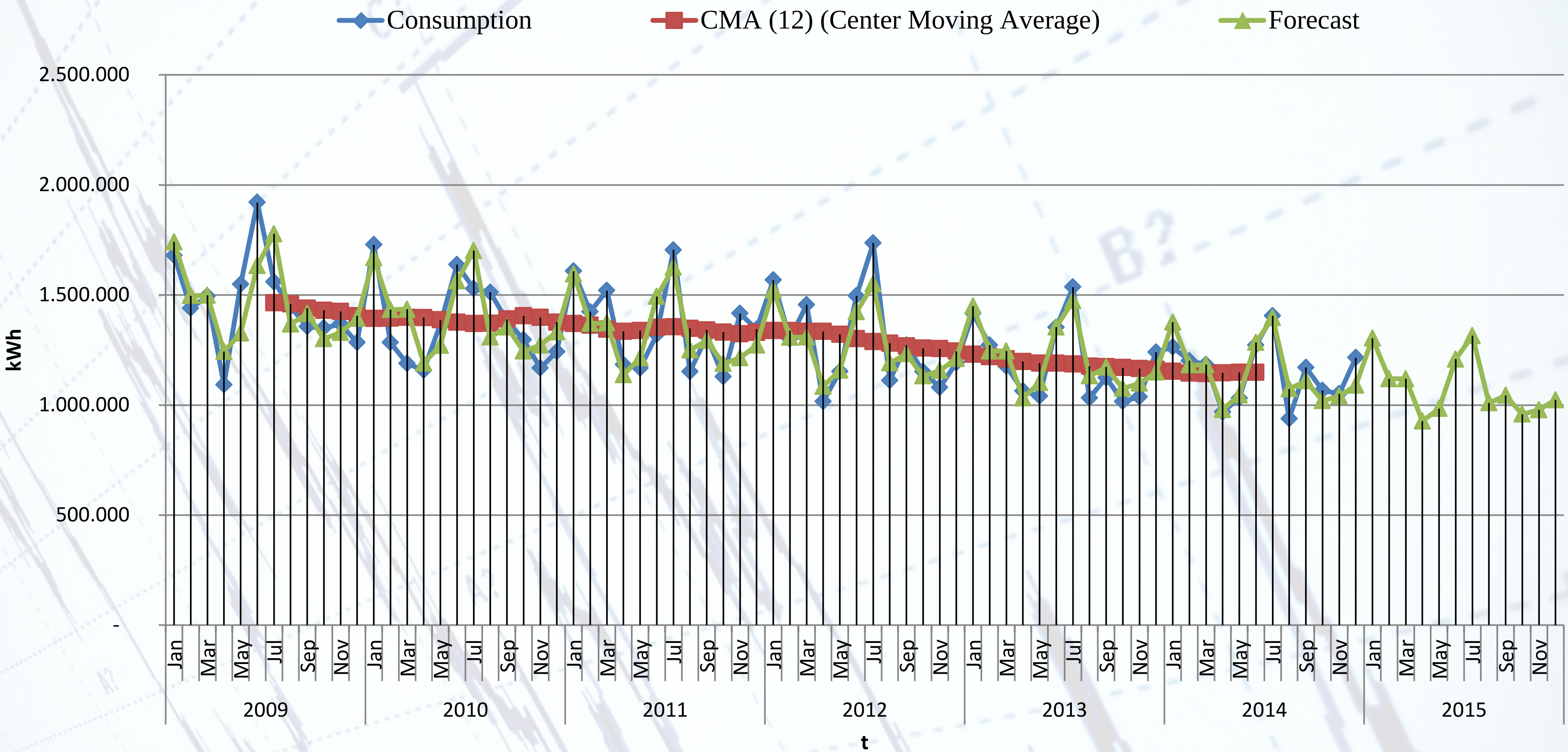
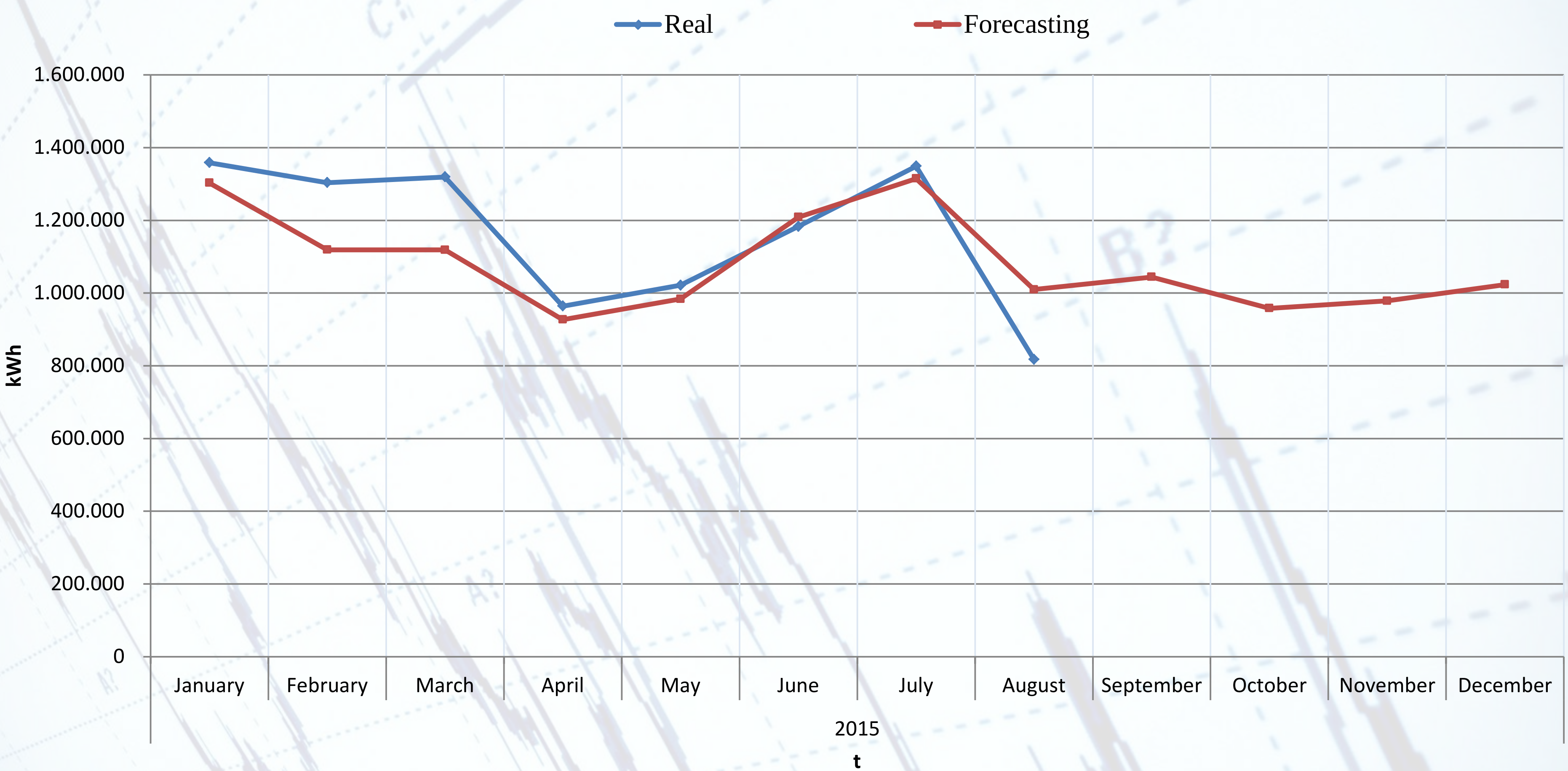


Evaluation Criteria	MAD	MSE	RMSE	MAPE	MPE
Time Series Decomposition	78207	10229918270	101143	5,91%	-0,55%

Forecasting Results

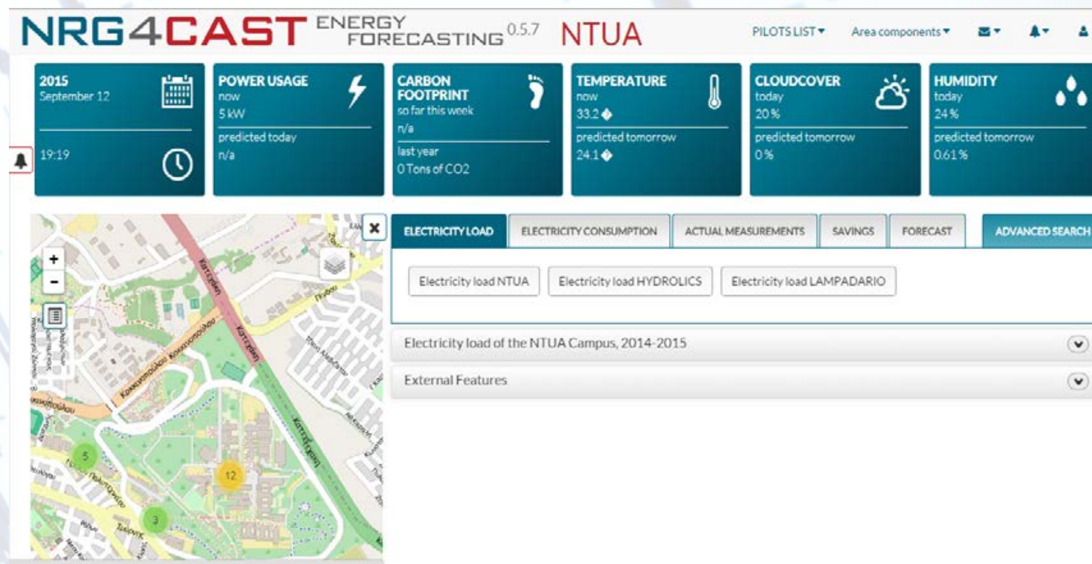


	January	February	March	April	May	June	July	August	September	October	November	December
Forecasting	1.303.059	1.119.009	1.118.868	927.068	983.618	1.208.727	1.314.754	1.009.792	1.044.019	958.207	978.411	1.023.456
Real	1.358.453	1.303.818	1.319.389	964.195	1.021.540	1.183.224	1.348.864	817.786				

NRG4CAST Project Platform

The NRG4Cast platform that has been developed is an advanced solution for predicting the behavior of local energy networks for the following scenarios :

- Data Access and Integration Platform
- User and Role Management
- Sensor and Information Source Registry
- Report Management and Visualization
- Event/Alert Processor
- Prediction Manager
- Real-time Visualization



THANK YOU

FOR YOUR ATTENTION