Seismic Time Series Analysis

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Introduction

Lockdown influence on seismic surveys

COVID-19 outbreak

 $\downarrow \downarrow$

Belgium Lockdown (March 14th, 2020)

 $\downarrow \downarrow$

Influence on background noise



Human activity correlation

Introduction

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Royal Observatory of Belgium Seismology-Gravimetry



9 stations



2 selected

Uccle in Brussels

Membach mountain area near a national park

(min, max) displacements

second precision

UTC times

missing values

 \rightarrow total displacement (difference)

ightarrow hourly mean

ightarrow legal-time conversion

→ fill with weekly mean (when needed)

Dataset division

Introduction

We want to be able to verify our models on pre-lockdown data



Fit on training \rightarrow validate on test \rightarrow assess lockdown influence

Seasonality - Visual inspection

$\begin{tabular}{ll} \mbox{Plot review} \\ \mbox{ψ} \\ \mbox{Daily and weekly seasonalities} \\ \end{tabular}$

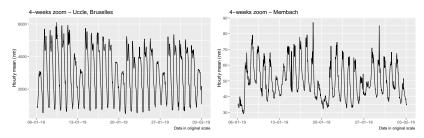
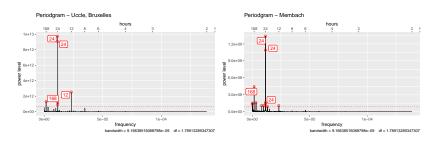


Figure: Zoom from January 6th to February 3rd 2019

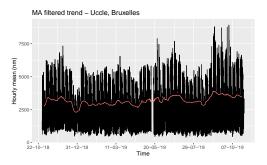
Seasonality - Periodgram

Fourier Transform with different frequencies United Property Pr



Decomposition - Trend extraction

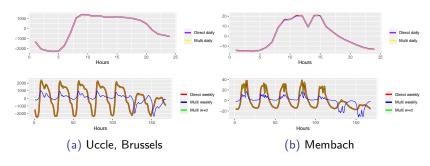
Tested simple, Spencer's and Moving Average filters

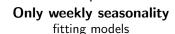




Decomposition - Seasonality extraction

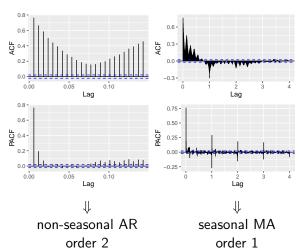
MA filter for detrending + local mean method





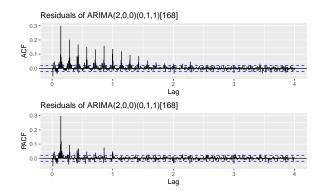
Uccle - ARMA orders

Figure: ACF and PACF plots after diff at lag 168



Uccle - Remaining seasonality

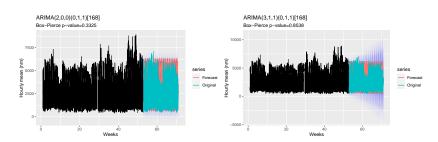
ACF and PACF plots highlight 24-hours seasonality on residuals



		(refit)	Box-Pierce
ARIMA	AIC	MAPE	p-value
$(2,0,0)(0,1,1)_{168}$	119700.1	5.89%	0.333
$(3,1,1)(0,1,1)_{168}$	119513.4	6.10%	0.854
$(4,1,2)(0,1,1)_{168}$	119396.9	6.13%	0.109

Other models have higher AIC and MAPE, while p-value < 0.05

Uccle - Models validation



	ARIMA	MAPE	80% CI	95% CI
accepted model \Rightarrow	$(2,0,0)(0,1,1)_{168}$			
	$(3,1,1)(0,1,1)_{168}$	15.18%	pprox 96%	pprox 98%
	$(4,1,2)(0,1,1)_{168}$	14.68%	pprox 98%	pprox 99%

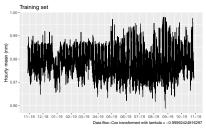
Membach - Data transformation

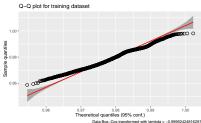
Spikes in data make it heavily non-Normal

↓

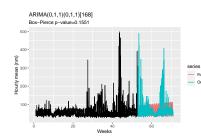
Transform using Box-Cox with $\lambda \approx -1$ Safe since all our data is positive

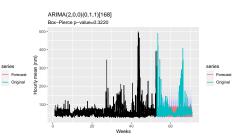






Membach - Models validation

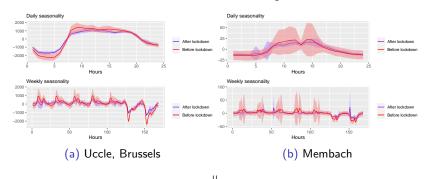




	ARIMA	MAPE	80% CI	95% CI
	$(0,1,0)(0,1,1)_{168}$	17.25%	pprox 99%	100%
	$(0,1,1)(0,1,1)_{168}$	17.98%	$\approx 98\%$	$\approx 99\%$
$accepted model \Rightarrow$	$(2,0,0)(0,1,1)_{168}$	16.14%	pprox 73%	$\approx 89\%$

Multiple seasonalities

Seasonalities extracted together

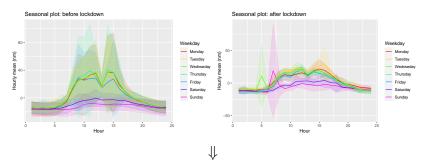




No significant difference

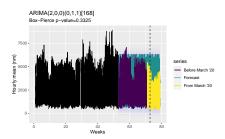
Weekly seasonality

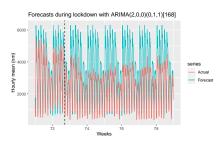
Only weekly seasonality extracted



Monday to Friday lower values Overall flattening towards 0

Forecasts assessment



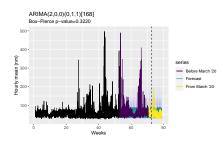


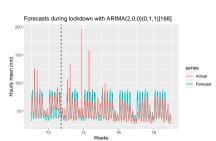
Uccle, Brussels lockdown → during lockdown

MAPE 16% → 46% 80% CI 73% → 39% 95% CI 89% → 63% ↓

Performance degradation

Forecasts assessment





Membach

lockdown → during lockdown

MAPE $17\% \to 14\%$ **80% CI** $81\% \rightarrow 82\%$ **95% CI** $91\% \rightarrow 96\%$



Slight performance improvement lower peaks

Models performance

- Periodgrams and models confirm weekly and daily seasonality
- Both chosen models have interesting forecasting power Missed daily seasonality
- Models have **same number of parameters** for each component *Membach data is transformed*
- Stable seasonality explains most of the variability Membach peaks not explained

Lockdown influence

Mixed findings:

- Influence results non-significant on seasonality
- Influence on forecasts depends on the station
 Correlation with station location

Future Works

- Models with **multiple seasonality** components *MSTL*, *TBATS*, *ARIMA with Fourier Terms*, ...
- Analysis on the other **7 stations**
- Analysis when > 2 years of data available
- Different factors modify lockdown impact Location, dimension of nearest city, ...

Thank you for your attention

