SARIMA models for early estimates of energy balance statistics

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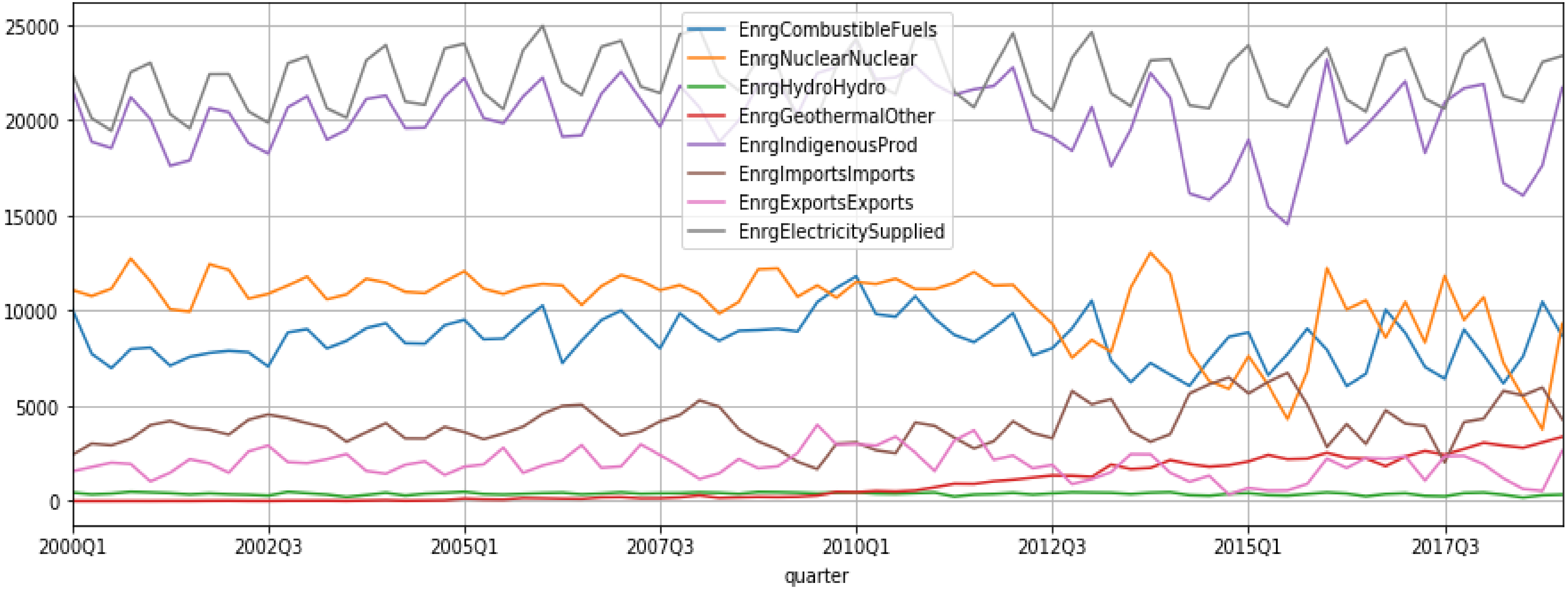
Introduction

- Anneleen Goyens and Bart Buelens are in the process of publishing *Early estimates of energy balance statistics using machine learning*
- In their paper, they used machine learning models to forecast energy balance series
- For the sake of comparison, I forecasted the same series but using classical Time Series Methods
- I used Exponential Smoothing Models and also SARIMA models
- In this talk, we will show the SARIMA models selected and compare their performance with the ML models

Overview of the Data

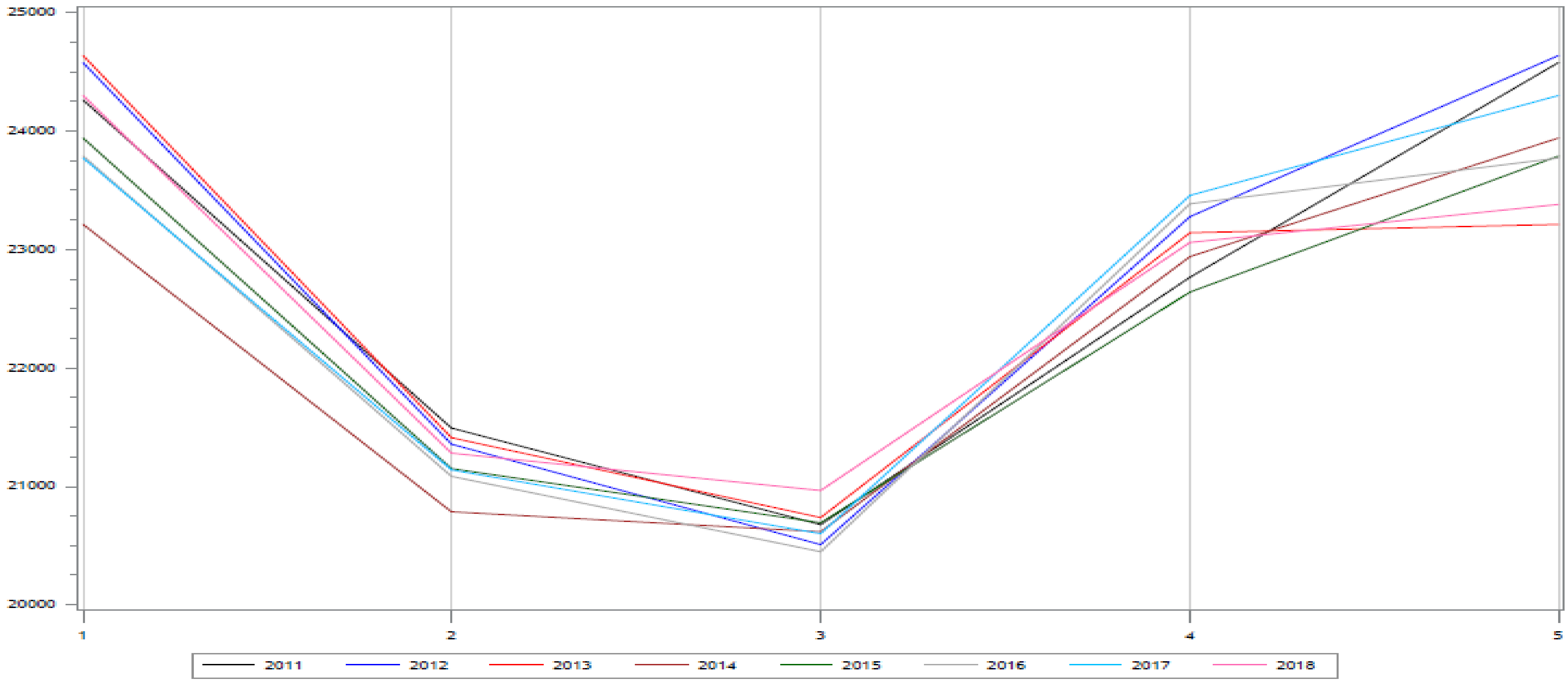
- Quarterly data
- Eight target series in GWh: Combustible Fuels, Hydro, Geothermal/Other , Indigenous Production , Imports, Exports , Electricity Supplied
- Some auxiliary variable (Economic, Weather variables)
- Data is from 2000Q1 to 2019Q1
- Training dataset: from 2000Q1 until 2015 Q1
- Test dataset: from 2015Q2 to 2019Q1
- All eight target series are seasonal

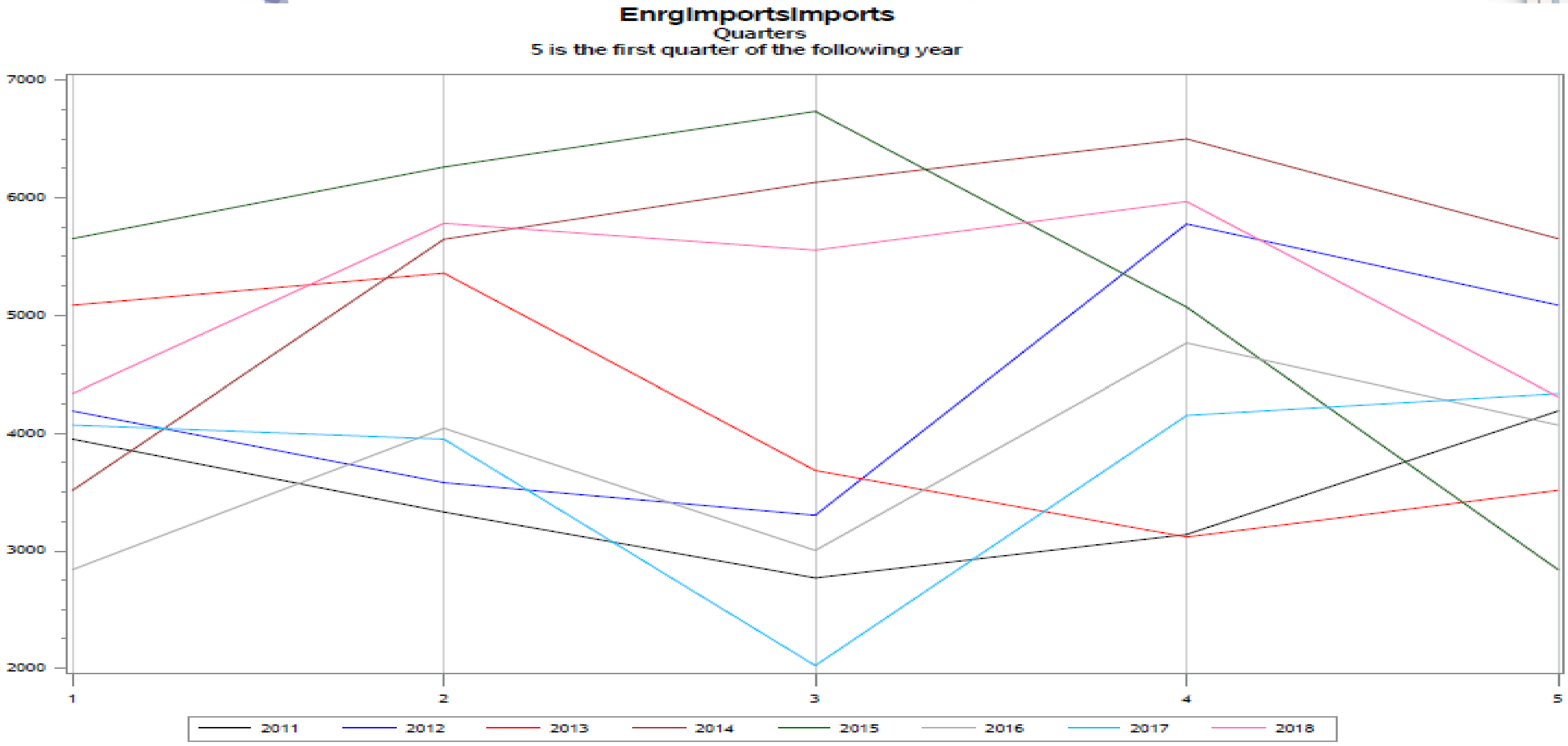

EnrgCombustibleFuels
EnrgNuclearNuclear
EnrgHydroHydro
EnrgGeothermalOther
EnrgIndigenousProd
EnrgImportsImports
EnrgExportsExports
EnrgElectricitySupplied
25000
20000
15000
10000
5000
0
2000Q1
2002Q3
2005Q1
2007Q3
2010Q1
2012Q3
2015Q1
2017Q3
quarter

EnrgElectricitySupplied

Quarters

5 is the first quarter of the following year




EnrgImportsImports
Quarters
5 is the first quarter of the following year
7000
6000
5000
4000
3000
2000
1
2
3
4
5
2011
2012
2013
2014
2015
2016
2017
2018

Machine Learning Methods used in the paper

- Linear Model
- Ridge
- LASSO
- Random Forest
- Neural Net
- Ensemble (averaging of the above methods)

SARIMA Model selection

- Only the test data was used for the model selection and the parameter estimation
- The SARIMA models were selected using stationarity tests for the orders of differentiation and AIC tests were used for the order of the models
- Auxiliary variables were deemed not improving the model according to an AIC test so they were not used
- Forecasts were out-of-sample (only the training data was used in the forecast)
- The work done using the SAS® High-Performance Forecasting software

SARIMA models selected

Series	Model
Combustible Fuels	(0,1,1)x(0,1,0)
Nuclear	(3,1,0)x(0,1,1)
Hydro	(1,1,0)x(0,1,1)
Geothermal Other	(0,1,1)x(0,1,1)
Indigenous Production	(0,1,0)x(2,1,0)
Imports	(0,1,0)x(0,1,1)
Exports	(4,1,1)x(0,1,0)
Electricity Supplied	(0,1,0)x(0,1,1)

Comparison with Machine Learning Methods using the MAPE

	SARIMA	Linear Model	Ridge	LASSO	Random Forest	Neural Net	Ensemble
Combustible Fuel	8.3%	13.5%	14.6%	18.2%	14.1%	18.5%	13.8%
Electricity Supplied	1.6%	3.0%	4.2%	4.7%	1.5%	1.6%	1.7%
Exports	78.5%	91.1%	69.7%	74.1%	70.5%	58.1%	62.9%
Geothermal	11.6%	80.6%	15.0%	15.6%	26.0%	42.1%	34.2%
Hydro	14.8%	23.2%	18.3%	22.5%	18.2%	36.9%	22.8%
Import	59.5%	25.3%	44.6%	50.3%	39.7%	32.3%	34.9%
Indigenous	24.6%	14.9%	10.7%	11.1%	10.2%	11.1%	10.1%
Nuclear	39.0%	47.5%	33.3%	32.2%	31.6%	34.1%	32.4%

Baseline model

- In the paper, the ML models are compared with a baseline model “yminus 4” which means using the value of the same quarter of the previous year
- “yminus4” is equivalent to a SARIMA model (0,0,0)x(0,1,0) model which is the simplest SARIMA model
- SARIMA models are well established and there are fairly automated procedures (such HPF in SAS and auto.arima() in R) to select the models
- SARIMA models can be used as a benchmark to evaluate if a machine learning algorithm can improve accuracy when forecasting time series
- Alternatively an “Airline model” (0,1,1)x(0,1,1) could be used as a baseline model

Conclusion

- Based on those eight series, no method is clearly the best in all situations
- SARIMA seems to be doing better for series with a clear seasonal pattern
- There are well established automated SARIMA model selection methods in several software
- Such SARIMA model could be used as benchmark (in addition to “yminus4”)