EDA

Allan

2023 - 06 - 14

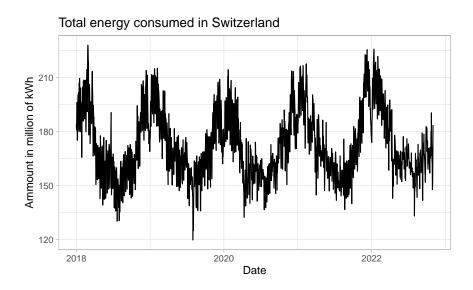
Contents

The Data we have :

time	end_users_cons	$energy_prod$	energy_cons	pos_second	${\rm neg_second}$	pos_tertiary	neg_tertiary
2015-01-01 00:15:00	1790683	1697772	1922526	37500	0	0	0
2015-01-01 00:30:00	1777126	1686388	1907138	22200	0	0	0
2015-01-01 00:45:00	1807976	1724777	1940146	36100	0	0	0
2015-01-01 01:00:00	1784944	1690007	1918599	16400	0	0	0
2015-01-01 01:15:00	1813997	1681642	1954830	52700	0	0	0

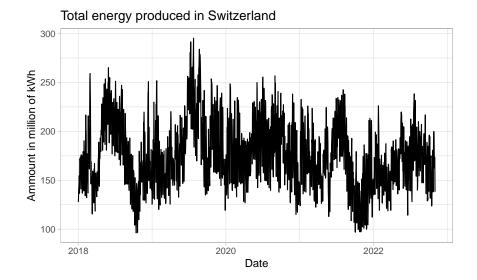
${\bf Quick\ overlook}:$

Dayly Consumption in Million



 \rightarrow Strong season lity, no obvious trend \rightarrow seems to have diffent level of season lity but hard to get due to the scope

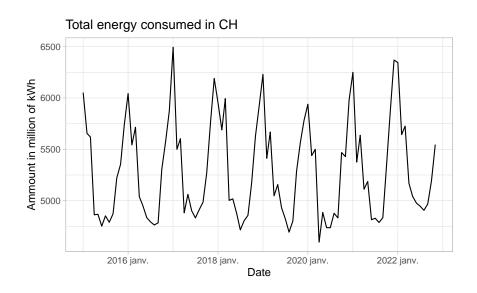
Dayly Production



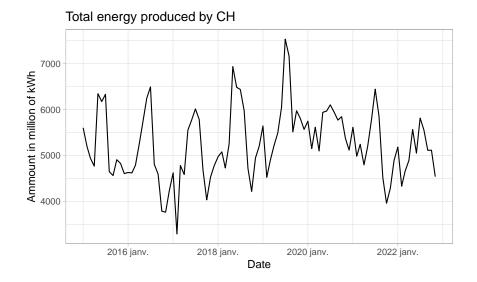
 \rightarrow also Strong seasonlity, no obvious trend but more messy \rightarrow seems to have diffent level of seasonlity but hard to get due to the scope

Zoom in to see the monthly seasonality

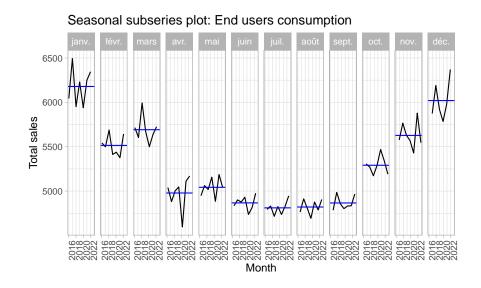
Monthly



Strong seasonality, no trend, peaks in Winter, lowest in sommer

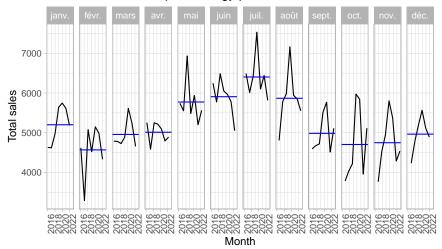


opposite of consumption, Strong seasonality, no trend, peaks in Summer, lowest in winter

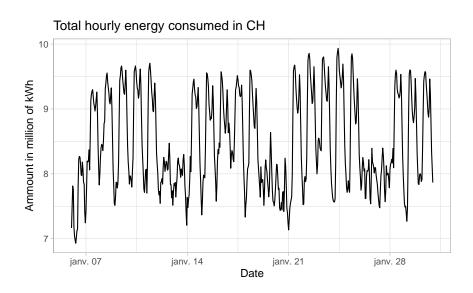


Better view that confirmed what we previous said for consumption

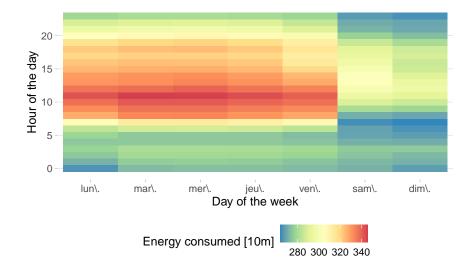
Seasonal subseries plot: Energy production



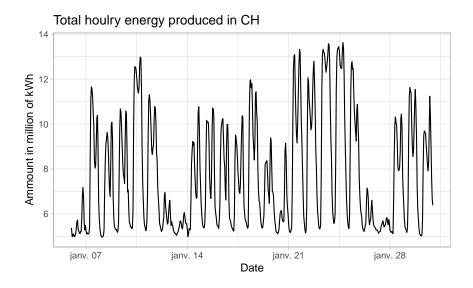
Better view that confirmed what we previous said for production Zoom in to see the weekly seasonality



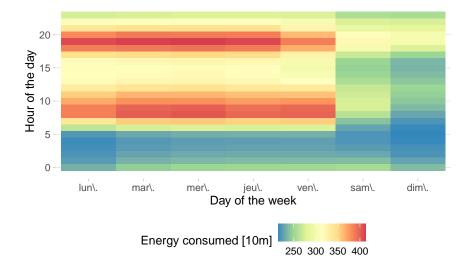
We can see here both weelky and daily season laty : With peaks during days (morning and end of afternoon) and during week with higher volume on week day (no significant difference among days themselves)



Trend is generalized through the whole period, peaks around noon

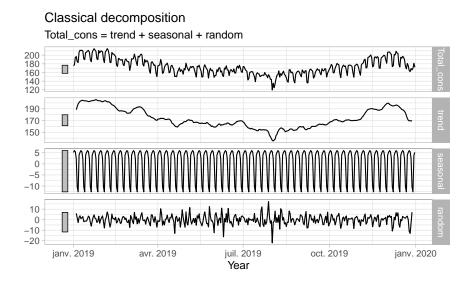


same conclusion as consumption



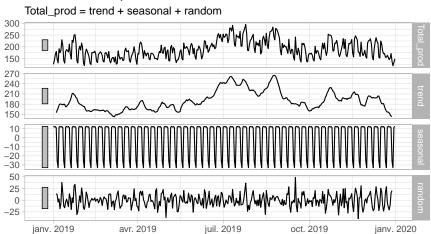
Trend is generalized through the whole period, peaks around 9am and 7pm, almost 0 prod btw 0 and 5 am \rightarrow noise and poeple aint working

We can now build the stl decomp with additive parameter due to no change over time in the seasonlity :



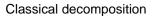
We reduce the scope to a year the have a better a view of the data, we have shown that seasonality was constant over the year. also show us the weekly seasonality

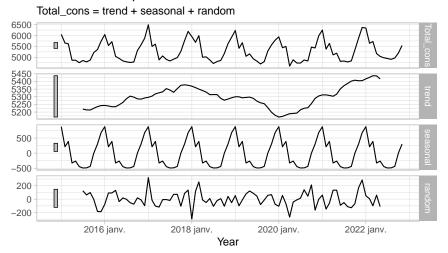
Classical decomposition



Year

Same for production

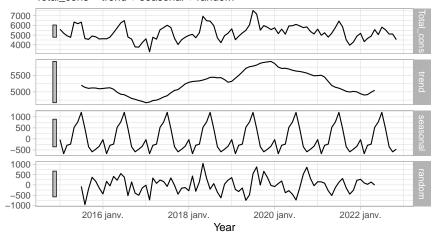




Monthly seasonality for cons

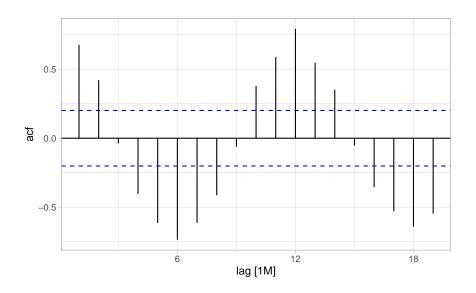
Classical decomposition

Total_cons = trend + seasonal + random

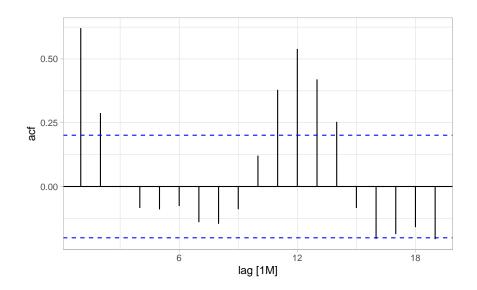


Monthly seasonality for prod

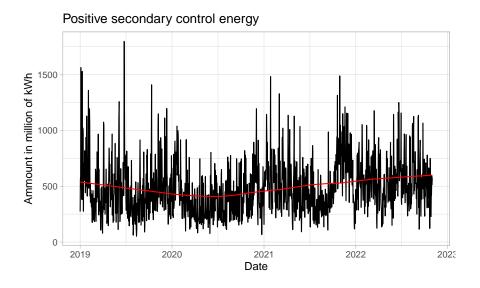
Let's have a look at the residuals :

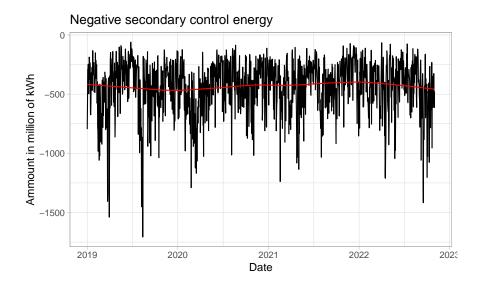


for cons



for prod
Positive and Negative Secondary control with trend





Positive and Negative Tertiary control with trend