

Influence of large-scale weather patterns on power system imbalance forecast errors in Sweden

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Introduction

To what extent does the synoptic weather situation affect the difficulty of balancing the Swedish national power grid proactively using cost efficient reserves?

European balancing market functions are being implemented with:

- Automated procurement
- Decisions based on data driven forecasting models
- Imbalance volumes are determined per bidding area (see Figure 1 below) in real-time

Simultaneous increase in VRE penetration:

- In 2025, roughly 24% of Sweden's electricity production¹ originated from wind power
- Recent installations have been located in the northern parts of Sweden upholding the historic asymmetry between supply and demand

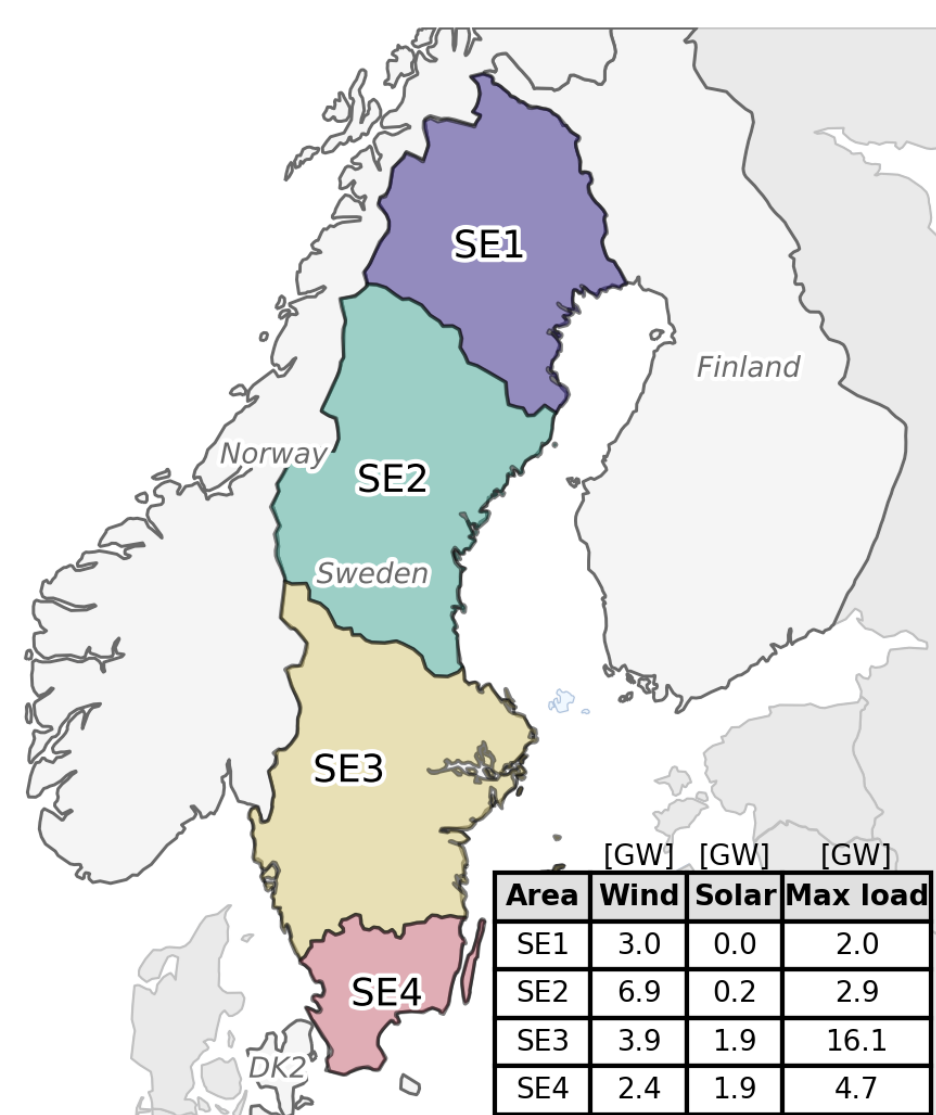


Figure 1: Map of Scandinavia showing Sweden's bidding areas and data corresponding to VRE generation and demand.

Method

- Weather classes representing geostrophic flow directions are determined by applying **Jenkinson-Collison**² classification to hourly mean sea level pressure fields from MEPS forecasts³
- The output consists of binary classes (N,NW,W,...) along with a cyclonic (C), anticyclonic (A) and a low flow (LF) class

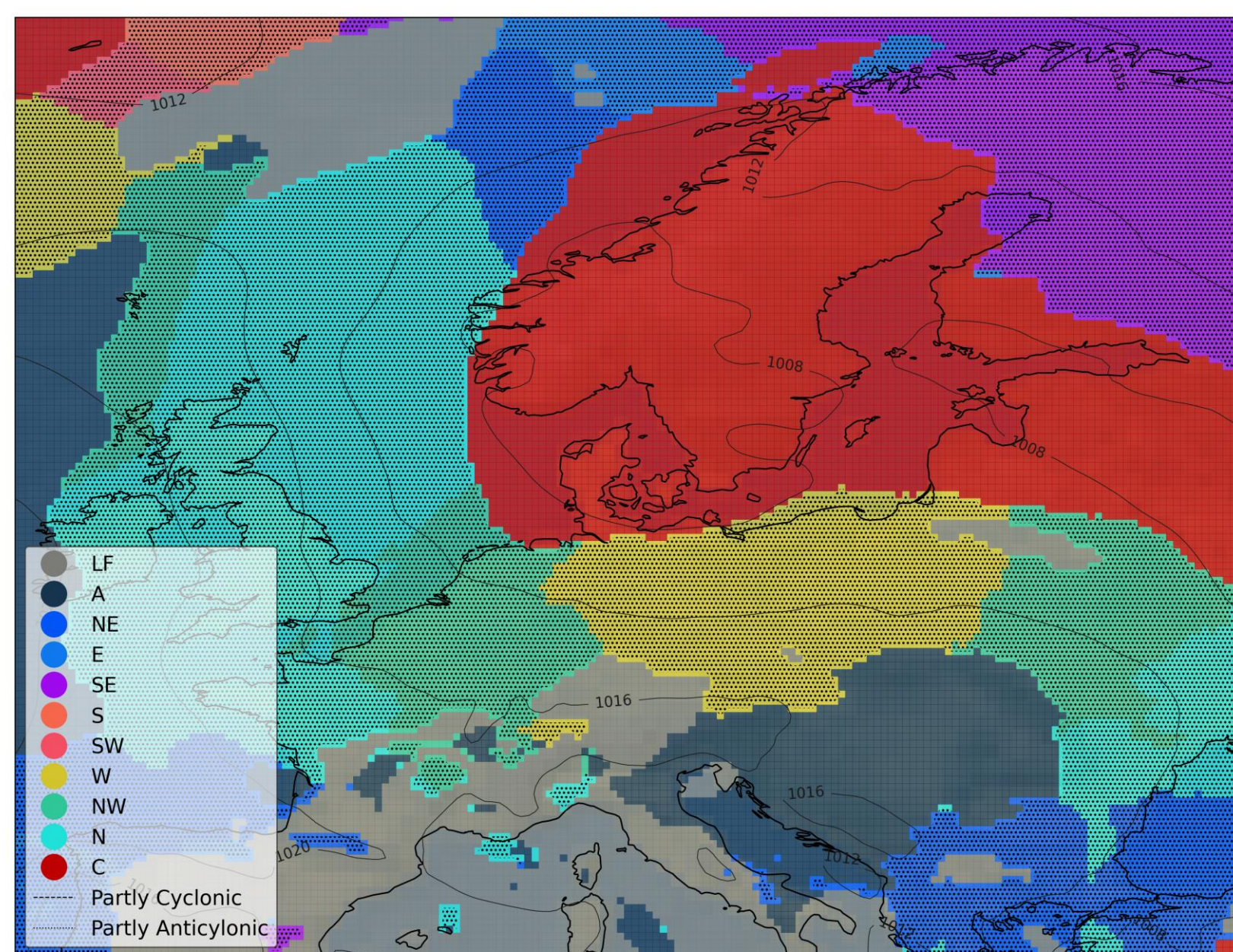


Figure 2: Example of output from Jenkinson-Collison classification algorithm, overlaid on map with MSLP lines.

The output is aggregated per bidding zone by "most frequent" and up-sampled temporally to match the imbalance forecast resolution

The imbalance forecast predicts ACE-OL (Area Control Error – Open Loop: the upcoming total balancing need in MW 20-35 minutes ahead, with already active regulations subtracted.

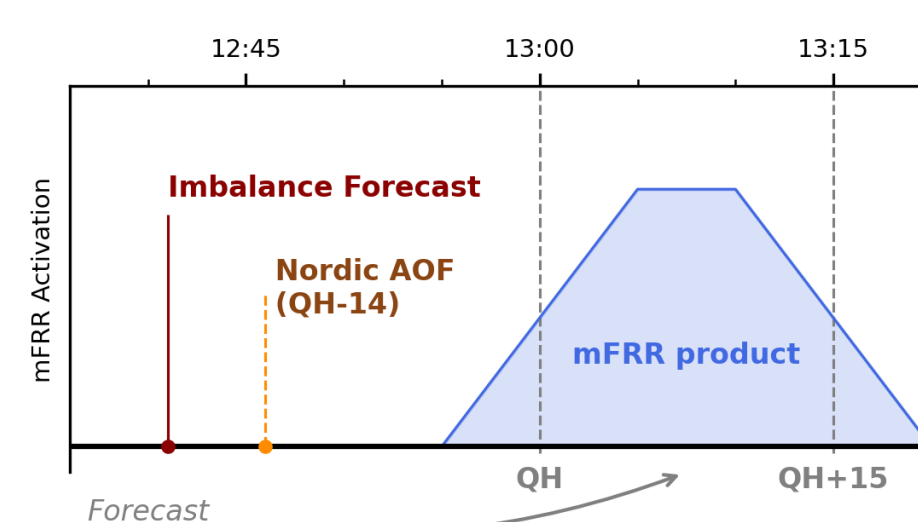


Figure 3: Timeline of the imbalance forecast and how it relates to the procurement algorithm (AOF) and the ramping of the balancing product manual Frequency Restoration Reserve (mFRR)

The forecasting problem:

- Short-term autoregressive time series
- Exogenous variables, e.g:
 - production plans
 - time of day
 - real-time data such as wind power measurements
- t_0 of the target signal is the most important

The forecast is evaluated through its absolute error

$$e_t = |y_t - \hat{y}_t|$$

And correlated with the weather classes

- Severe imbalances are considered in particular by comparing the 95th percentile of absolute forecast errors
- Block bootstrap resampling techniques are used to form uncertainty intervals while preserving temporal structures of synoptic weather

Results

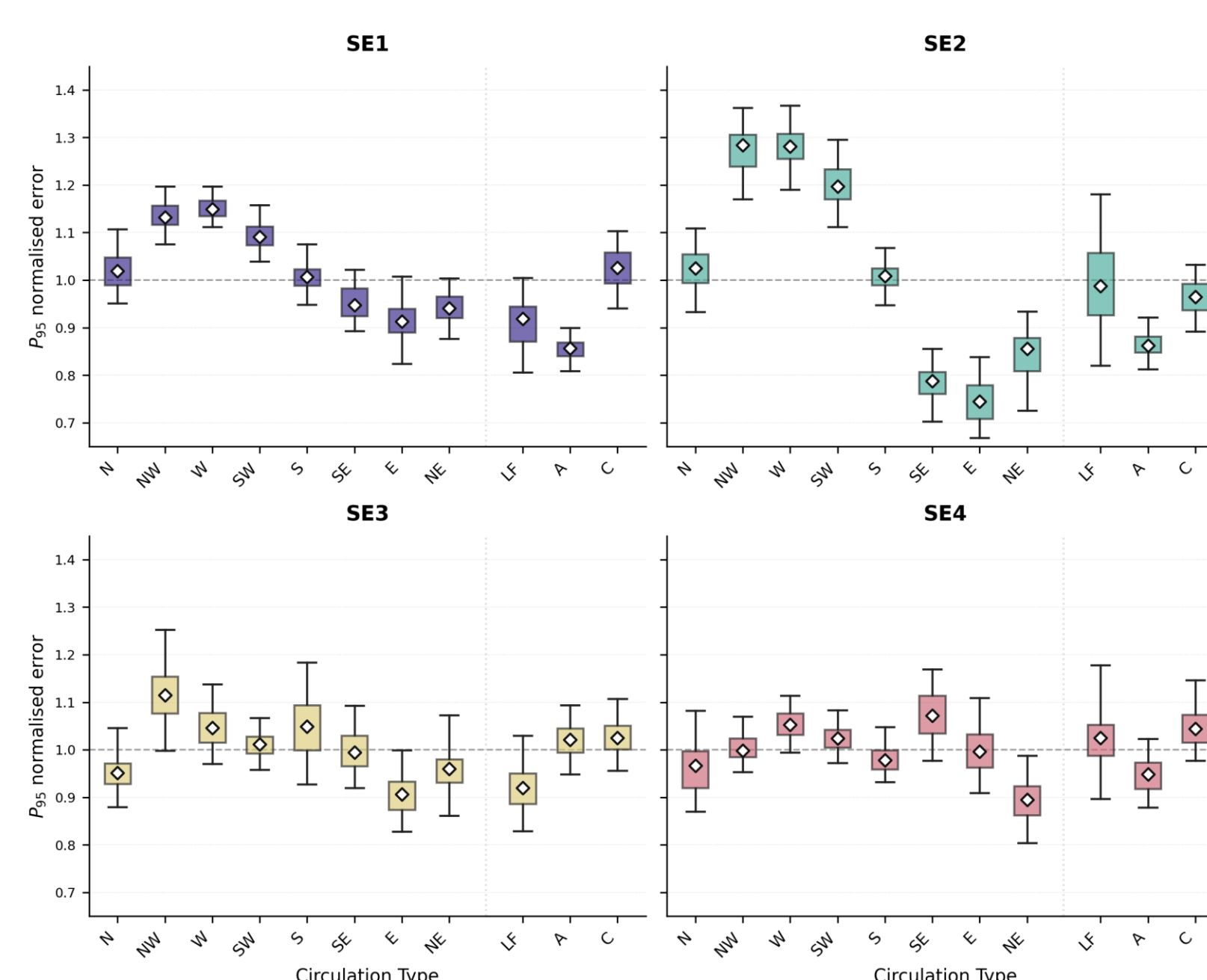


Figure 4: 95th percentile of the normalised absolute forecast error per bidding area and weather class. White diamonds represents the median, box represents the IQR and the whiskers represent the P2.5-P97.5 range.

- SE1 and SE2 show a clear dependency on flow direction while SE3 and SE4 do not.
- In SE1 and SE2, westerly flows correlate with large absolute forecast errors, and easterly and anti-cyclonic flow are associated with smaller absolute forecast errors

Identifying the meteorological drivers

- Build a Quantile Regression (QR) model where weather classes are represented by one-hot encoded features in X
- Fit model with absolute imbalance forecast errors as Y
- Null hypothesis by block shuffling X

.. then

- Add continuous weather parameters to the model in X (see table)
- Monitor the weighted standard deviation of the "weather class model coefficients"

Parameter	Abbreviation
Wind speed 100 m	WS WS ² WS ³
Wind direction 100 m	WD _{dir} WD _{cos}
Turbulence Intensity 100 m	TI
Relative humidity 2 m	RH
Accumulated total precipitation	TP _{log1p}
Total cloud cover	TCC
Surface SW downwelling radiation	SWDOWN
Surface air pressure	SP
Icing index 150 m	ICING
Temperature 2 m	T
Magnitude of pressure gradient	F

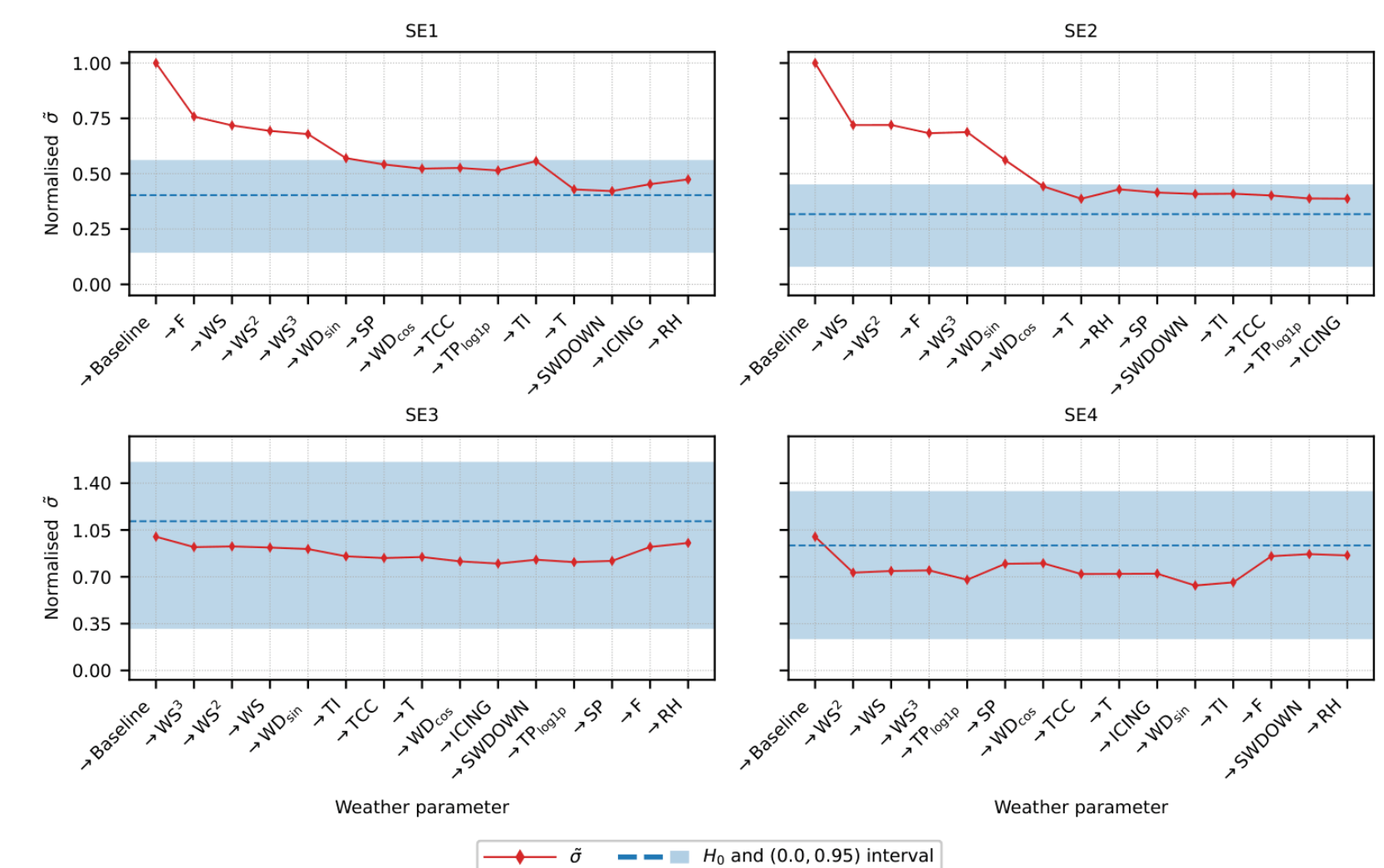


Figure 5: Normalised weighted standard deviation of weather class-coefficients as continuous weather parameters are added cumulatively to the QR model

The strong and significant drivers are wind speed and related variables which is clearly seen in SE1 and SE2 while statistically insignificant in SE3 and SE4.

Discussion and conclusions

- Automated and data driven proactive balancing in Sweden is affected by synoptic circulation types in SE1 and SE2 (Figure 4)
- The meteorological drivers are wind speed, wind direction and related variables (Figure 5)
- The strength of the effect relates to installed capacity of wind (Figure 1) but is also stronger for SE1 than SE3 with similar installed capacity, indicating that large demand-side may obscure imbalances caused by wind in southern Sweden

The results inform where improved wind power forecasts and meteorological observations would aid balancing the most, and indicate that dynamic dimensioning of reserves should take synoptic weather situation into account, as the power grid becomes increasingly weather dependent.

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Olle Viotti and Anna Rutgerström for valuable comments on the manuscript, MET Norway for maintaining the thredds API for access to Swedish weather data, Svenska kraftnät for funding the PhD project of the main author.

List of references

¹ Svenska kraftnät – Elstatistik: <https://www.svk.se/om-kraftsystemet/kraftsystemdata/elstatistik/>
² Jenkinson-Collison gridded python implementation by Pedro Lormendez: <https://github.com/PedroLormendez/jcclass>
³ Thredds API for access to MEPS forecasts: <https://api.met.no/product/THREDDS>



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