International Workshop on
Dynamic Stability Challenges of the Future Power Grids

Data-Driven and Machine Learning Methods for Power System Stability:

From Theoretical Foundations to Real-World Deployment

Presenter

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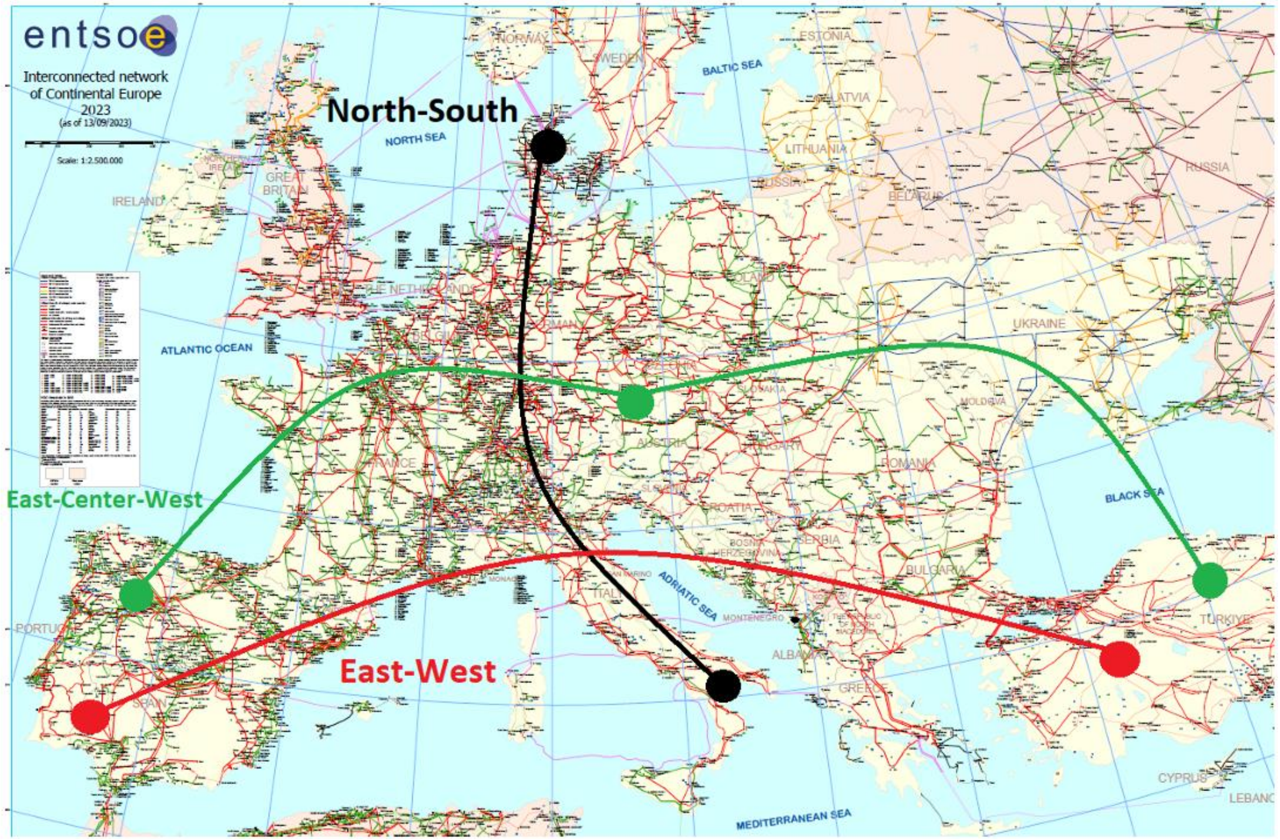
Contents

Comparative Analysis and Pratical Implementations of Data-Driven Methods for Electromechanical Oscillation Identification in Power Systems

01

European characteristic modes

- The Continental European Synchronous Area (CE SA) is characterized by different **interarea modes**: E-W, E-C-W, and N-S.
- To **detect** the presence and magnitude of such oscillations, the TSO monitors the network through WAMS.
- In this work, several advanced mathematical techniques such as Estimation of Signal Parameters via Rotational Invariance Techniques (**ESPRIT**), Tuft-Kumaresan (**TK**), and Stochastic Subspace Identification (**SSI**) are introduced and compared with respect to conventional techniques such as Dynamic Mode Decomposition (**DMD**) [1,2] and the combination of PCA with Prony (**PP**) [3].



Theory

1.1

Proposed approaches

ESPRIT is a high-resolution algorithm for estimating the frequency and damping of complex exponentials embedded in noise [4]. It exploits the **rotational invariance** property of signal subspaces derived from the covariance matrix.

$$H = \begin{bmatrix} x_1 & \cdots & x_{N-L+1} \\ \vdots & \ddots & \vdots \\ x_L & \cdots & x_N \end{bmatrix}$$

$$H = USV^*$$

$$U_s = U[:,1:r]$$

$$U_{s1} = U_s[1:L-1,:]$$

$$U_{s2} = U_s[2:L,:]$$

$$\mathrm{A} = U_{s1}^{\dagger} U_{s2}$$

$$p_i = \frac{\log(\lambda_i)}{\Delta t}$$

ESPRIT

TK is a **linear prediction** method that estimates the poles of a signal by solving a linear system constructed from samples [5]. The TK method is based on **autoregressive** modeling and the exploitation of the signal's linear prediction properties.

$$x(n) = \sum_{k=1}^{K} B_k z_k^n$$

$$x(n) = -\sum_{m=1}^{p} a_m x(n-m) + e(n)$$

$$x = -Ha + e$$

$$\hat{a} = argmin_a |x + Ha|^2$$

$$A(z) = 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_p z^{-p}$$

$$p_i = \frac{\log(\lambda_i)}{\Delta t}$$

TK

SSI is a data-driven approach used to extract dynamic system characteristics based solely on output measurements [6]. The SSI is based on the **discrete-time stochastic state-space model**.

$$x(k+1) = Ax(k) + w(k)$$

$$y(k+1) = Cx(k) + v(k)$$

$$H = USV^*$$

$$O \simeq U_r S_r^{1/2}$$

$$A \simeq \hat{A} = O_{s1}^{\dagger} O_{s2}$$

$$p_i = \frac{\log(\lambda_i)}{\Delta t}$$

SSI

Energy-based alarm

Once the dominant modes have been identified, the signal $x(t)$ can be approximated as a sum of these modes:

$$x(t) \simeq \sum_{i=1}^{r} X_i e^{p_i t}$$

The coefficients X_i can be estimated by solving a linear system involving a **Vandermonde matrix** constructed from the modal poles p_i. Each coefficient X_i is a complex number representing both the initial amplitude and phase angle of the corresponding mode.

Let us consider the mode $\widetilde{p_i}$ characterized by a specific frequency $\widetilde{\omega_i}$. The objective is to ensure that the **energy** of this mode remains low. To this end, the energy $\widetilde{E_i}$ can be computed as follows:

$$\widetilde{E_i} = \int_0^T \left|\widetilde{X_i} e^{\widetilde{p_i} t}\right|^2 = \left|\widetilde{X_i}\right|^2 \int_0^T e^{2Re(\widetilde{p_i})t}\, dt$$

The analytical solution is given by:

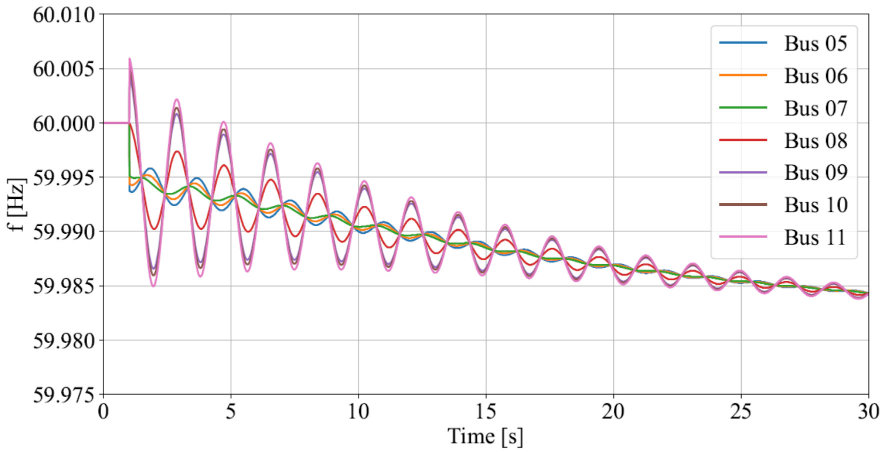
$$\widetilde{E_i} = \begin{cases} \left|\widetilde{X_i}\right|^2 \dfrac{e^{2Re(\widetilde{p_i})T-1}}{2Re(\widetilde{p_i})} & if\ Re(\widetilde{p_i}) \neq 0 \\ \left|\widetilde{X_i}\right|^2 T & if\ Re(\widetilde{p_i}) = 0 \end{cases}$$

Applications

1.2

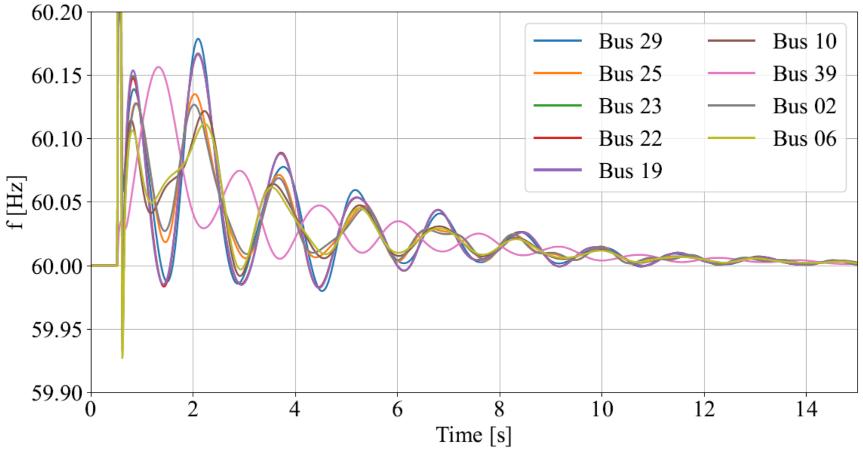
Benchmark systems

Two-area Kundur system



	MA	PP	DMD	SSI	ESPRIT	TK
f [Hz]	0.5431	0.5411	0.52	0.5432	0.5431	0.5434
ξ [%]	2.851	10.059	10.003	2.639	3.00	2.8273

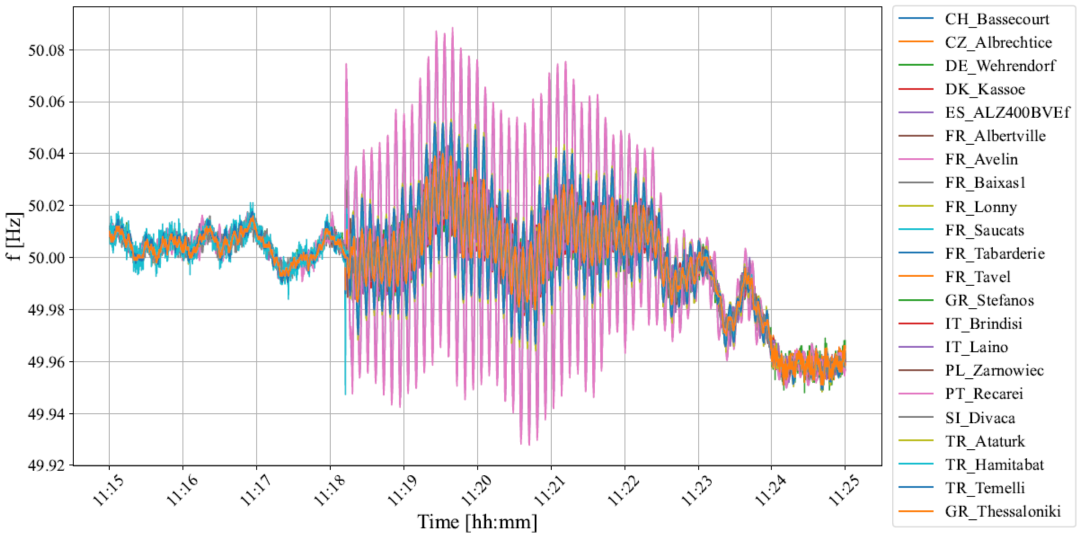
IEEE 39-bus system

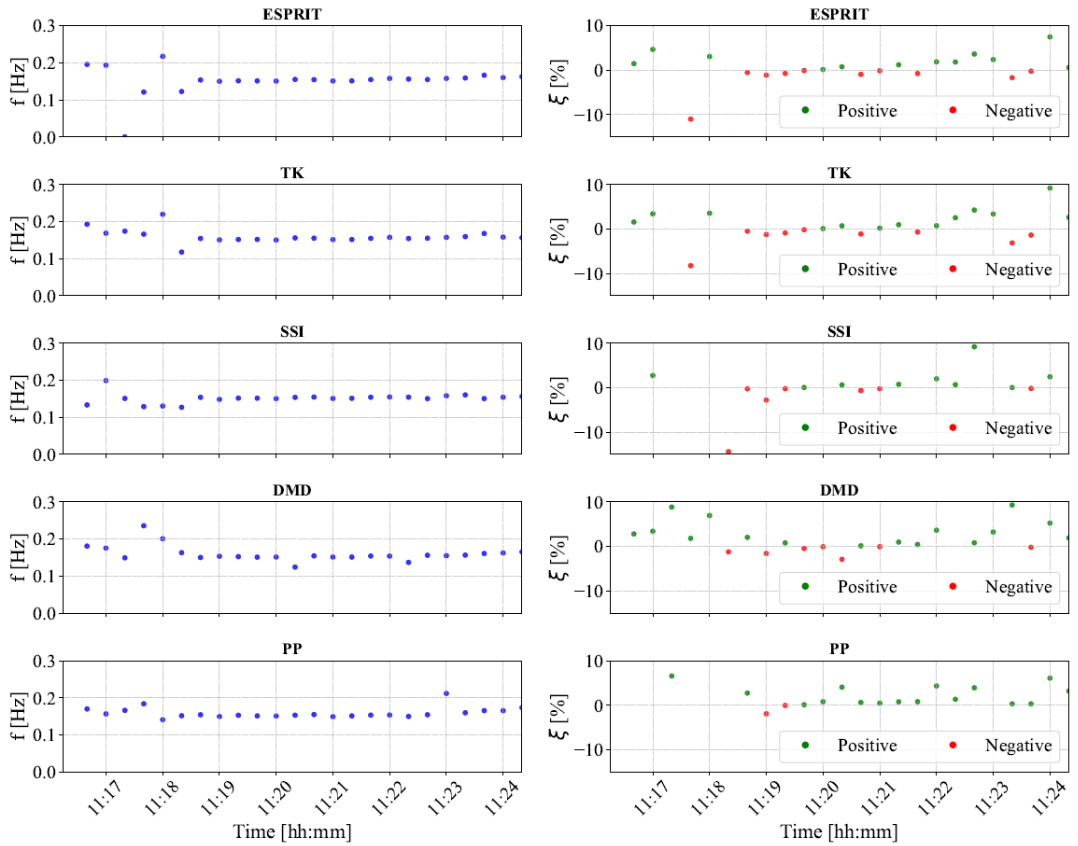


	MA	PP	DMD	SSI	ESPRIT	TK
f [Hz]	0.6385	0.6177	0.6857	0.6439	0.6381	0.6443
ξ [%]	7.799	22.27	14.95	10.35	7.67	8.825

Oscillatory event in the European power system on December 1st, 2016

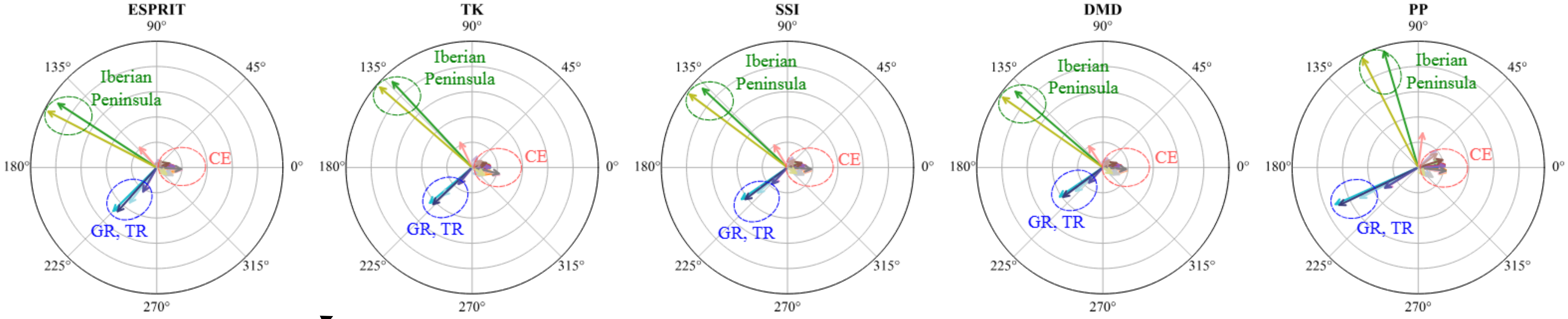
The first real-world event analyzed concerns the interarea oscillations that affected the European power system on December 1st, 2016.



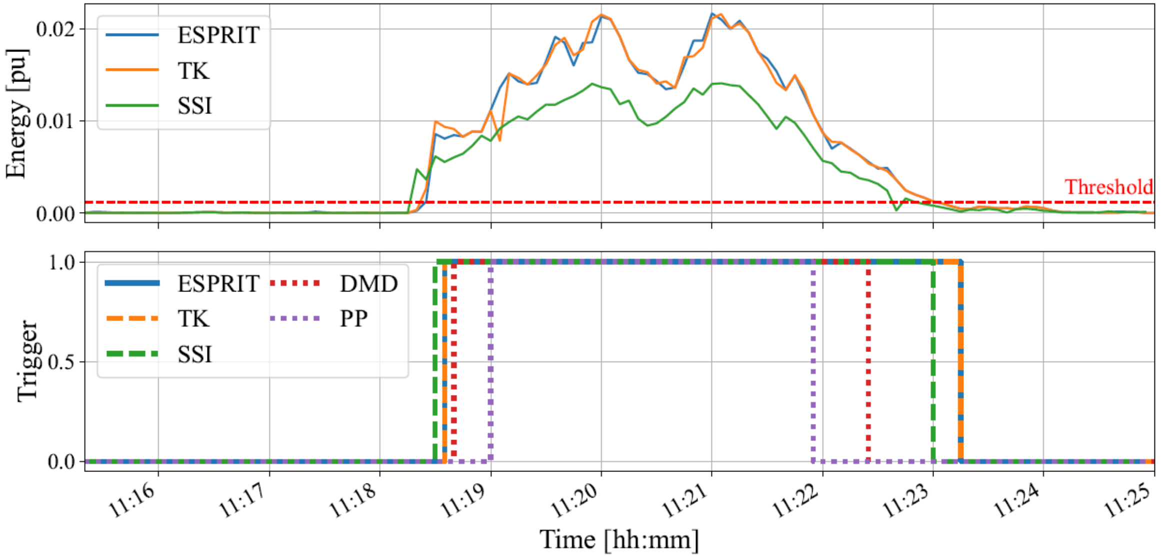


All methods consistently identified the **same frequency**; however, it is important to highlight the trend of the **estimated damping** values obtained through the novel approaches.

Oscillatory event in the European power system on December 1st, 2016



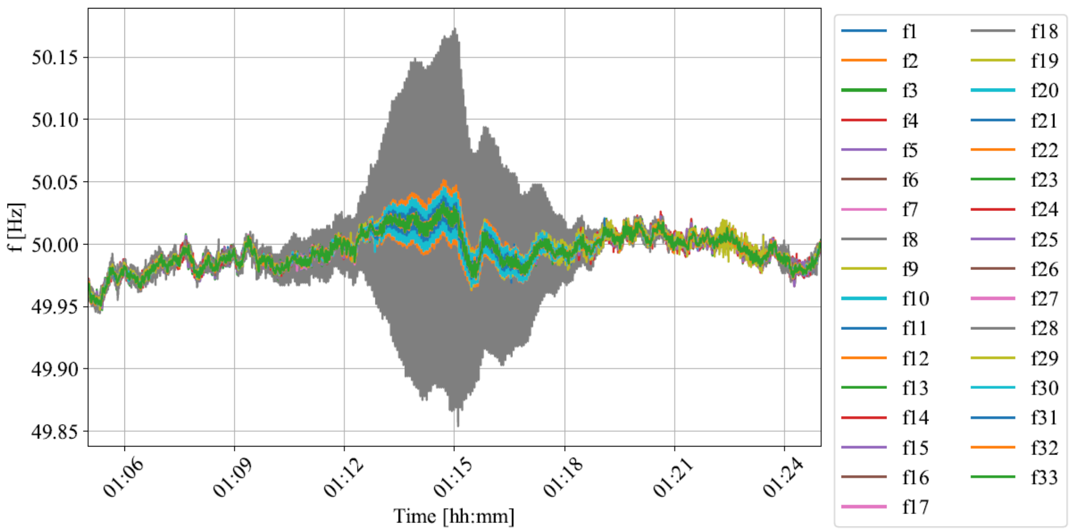
All approaches consistently identify **three oscillatory regions**: East, Central, and West (E–C–W).

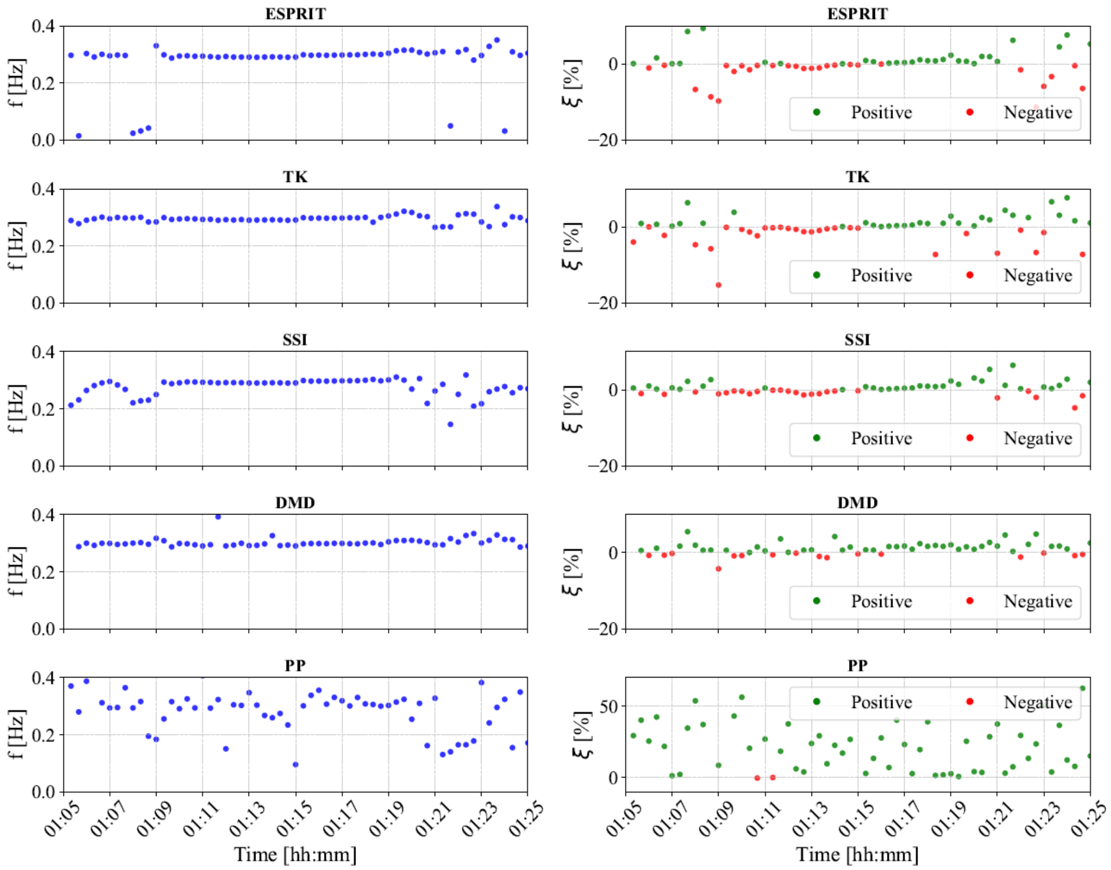


Energy-Based **Triggering** for Real-Time Applications

Oscillatory event in the European power system on December 3rd, 2017

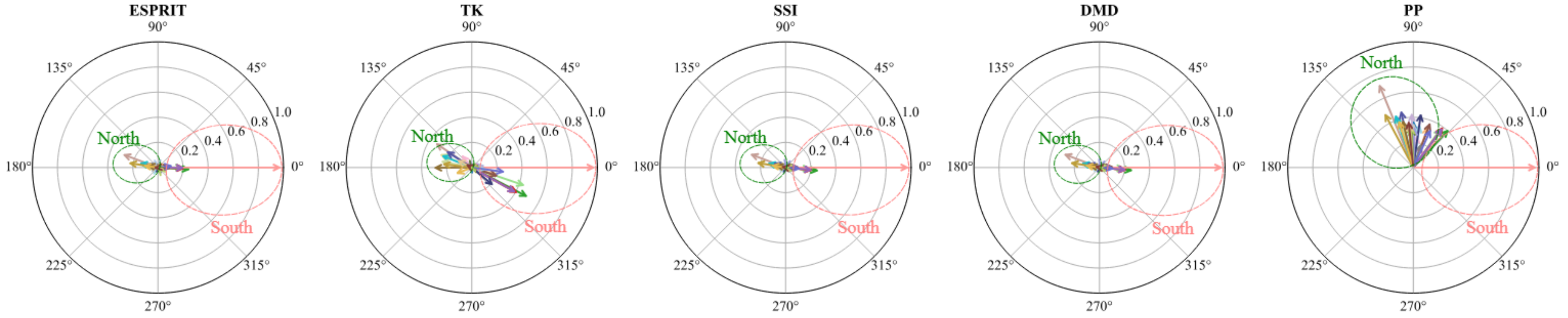
The second real-world event analyzed concerns the interarea oscillations that affected the European power system on December 3rd, 2017.



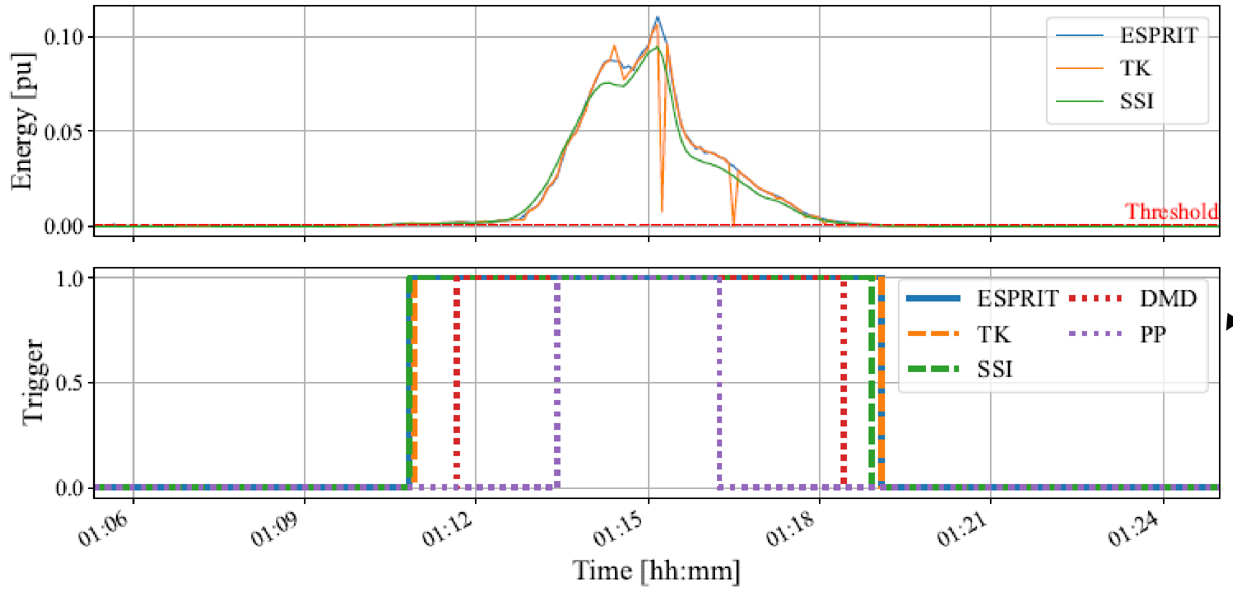


Even for this event, all methods consistently identify the **same frequency**. It is worth highlighting the trend in the **estimated damping** values.

Oscillatory event in the European power system on December 3rd, 2017

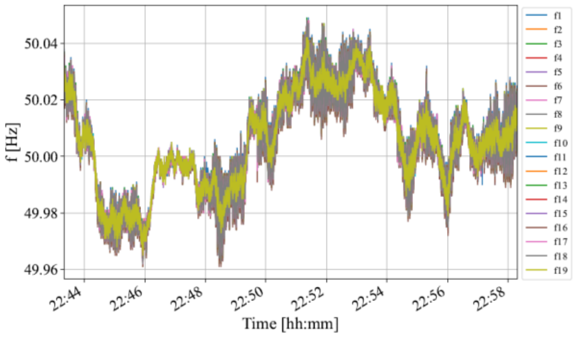


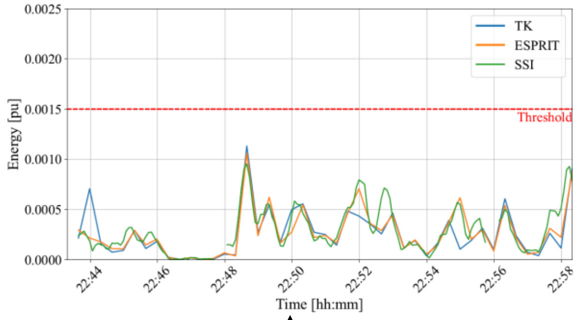
All approaches consistently identify **two oscillatory regions**, corresponding to the North–South (N–S) mode.



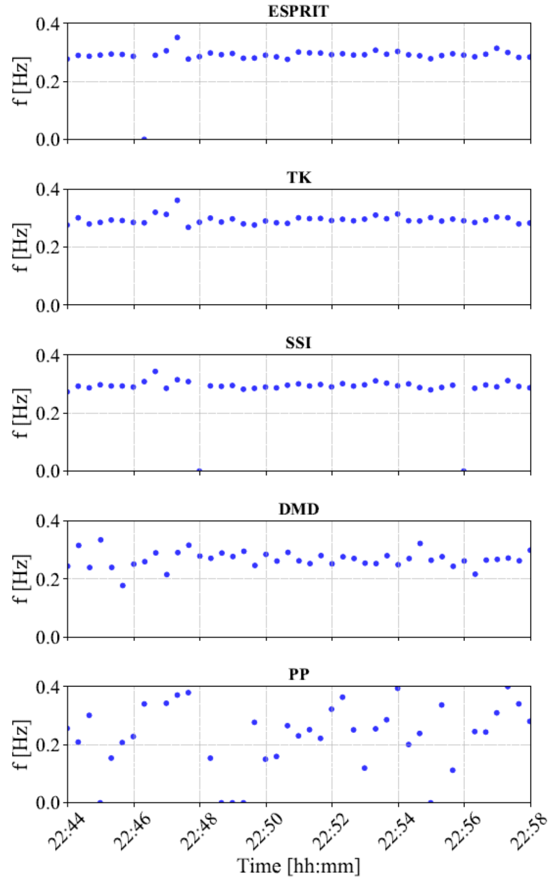
Energy-Based **Triggering** for Real-Time Applications

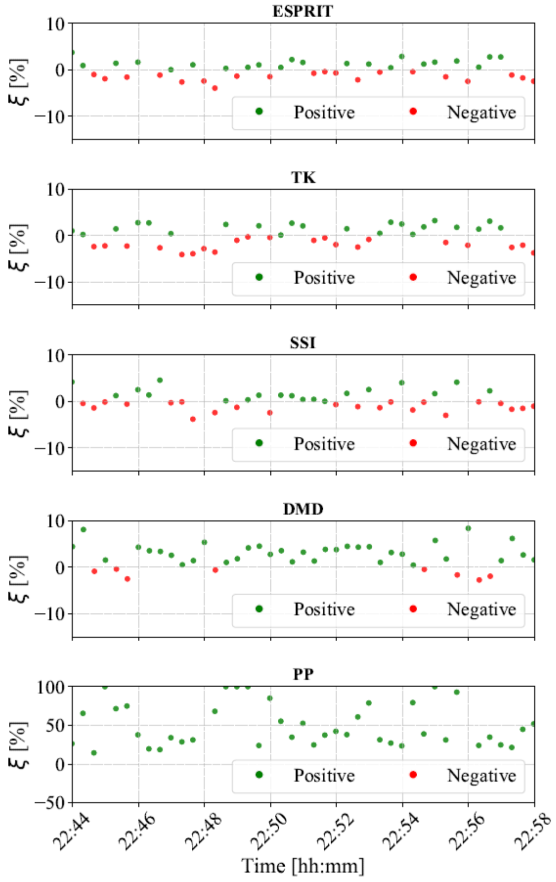
Normal grid operation in March 2021

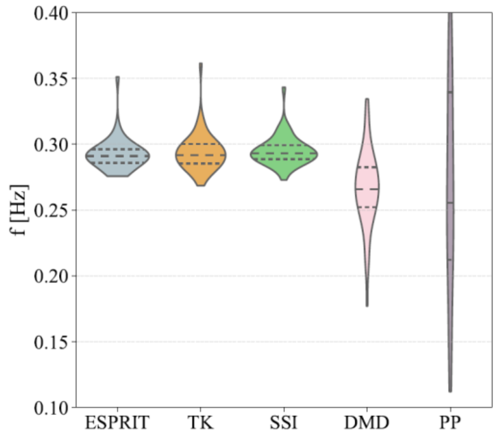


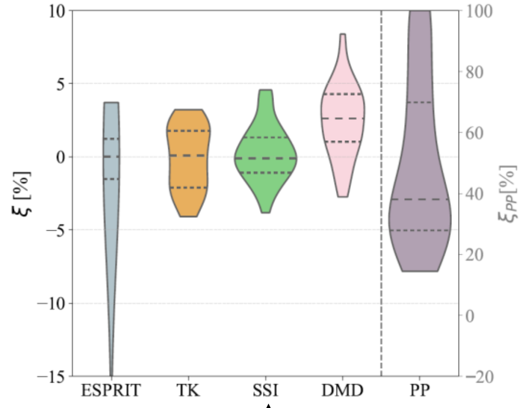


No False Alarms
Detected









$$x(t) = Ae^{-\xi t}\sin(\omega t + \phi) \xrightarrow{t \to \infty} \begin{cases} E = const & if\ \xi = 0 \\ E = 0 & if\ \xi > 0 \end{cases}$$

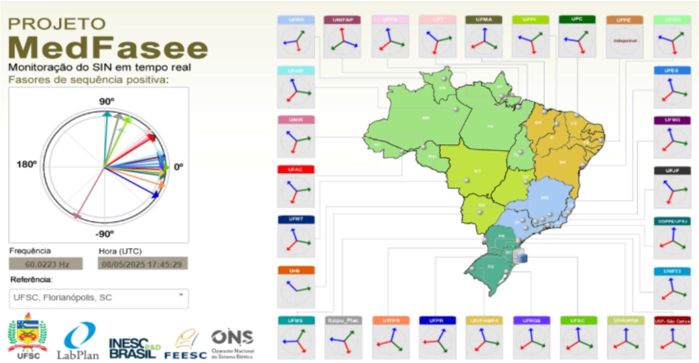
Violin plots of frequency and damping: ESPRIT, TK, and SSI all estimated **damping** values with a **median of zero** over a 15-minute time window.

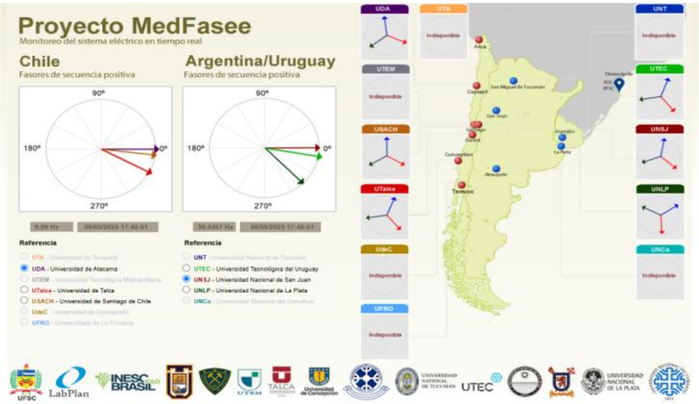
Iberian Power System Blackout on April 28th, 2025

- **MedFasee** is an **independent observatory** dedicated to monitoring power system dynamics, currently operating 40 PMUs across South America and 4 PMUs in Europe.

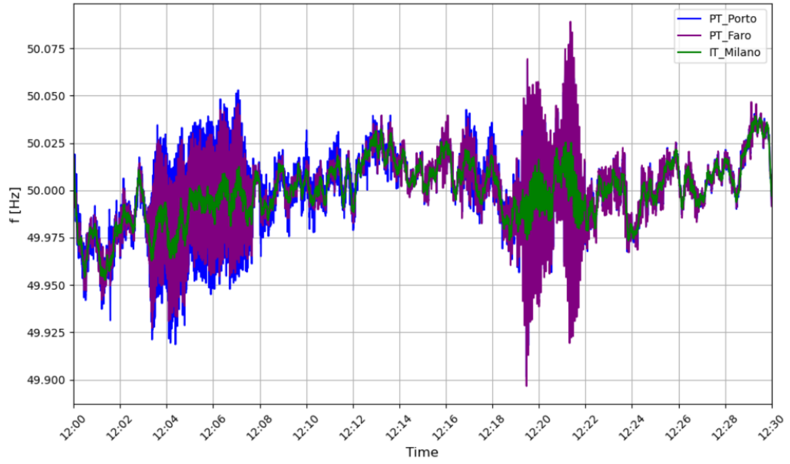
- The MedFasee project started with the partnership between **UFSC** and Reason through a public financing agreement (FINEP agency) in 2003.

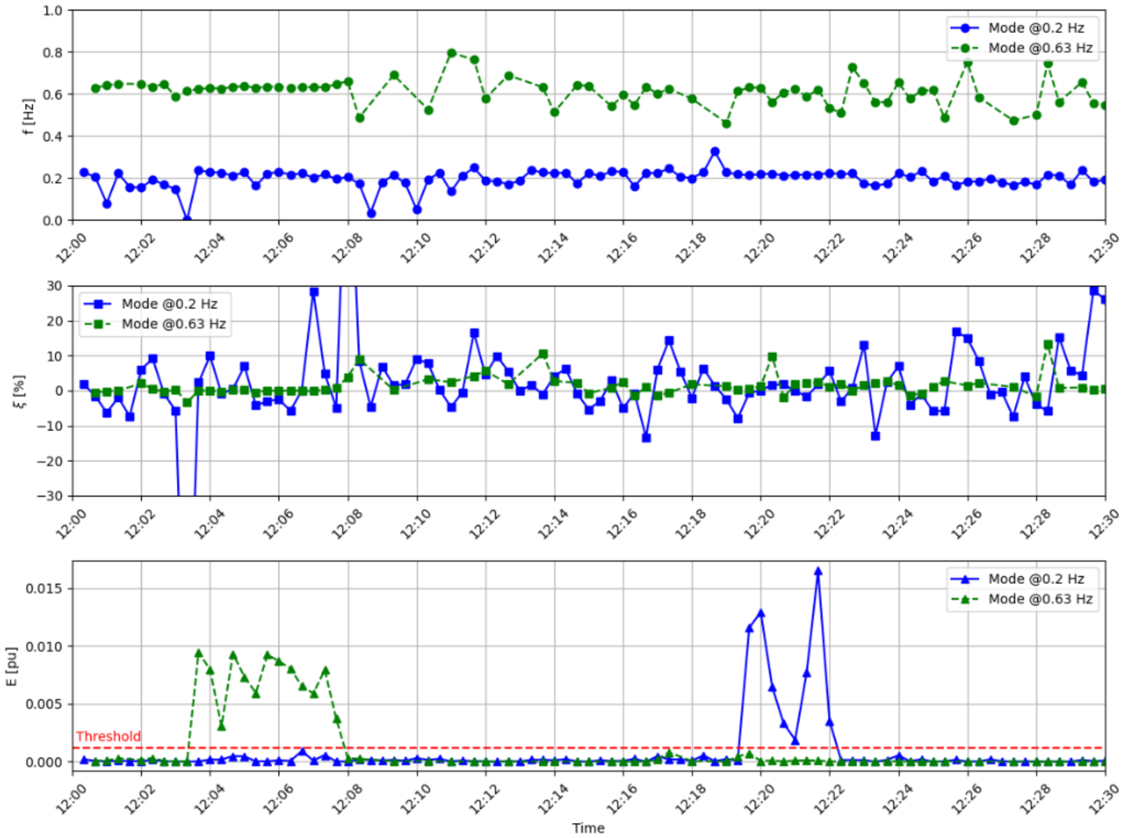
- Currently, three power system observatories are in operation: **Brazilian** observatory (medfasee.ufsc.br), **South American** observatory (medfasee.ufsc.br/conosur), and **European** observatory (medfasee.ufsc.br/europe).



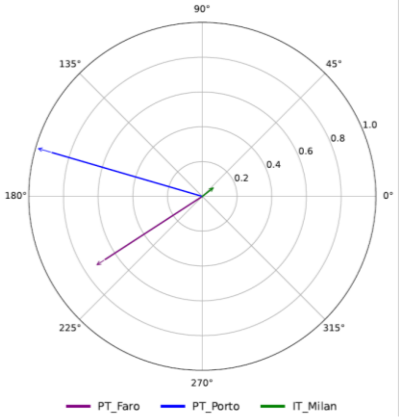


Iberian Power System Blackout on April 28th, 2025

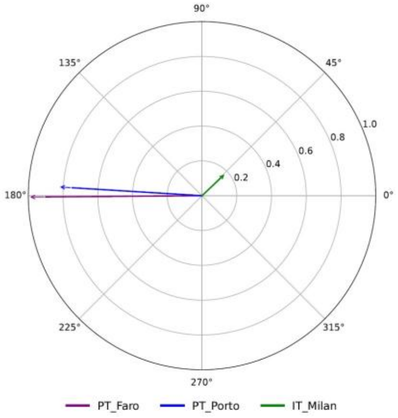




First oscillation @0.63 Hz



Second oscillation @0.2 Hz



The approach would have correctly **identified** the modes and **triggered** the alarm during both oscillatory events.

Conclusion

- In this work, **ESPRIT**, **TK** and **SSI** have been applied to study electromechanical oscillations in a power system.
- All the proposed approaches have been **validated** against modal analysis, which serves as the ground truth.
- They consistently demonstrate **superior performance** compared to state-of-the-art methods, particularly in estimating mode damping.
- The approaches have been tested on multiple **real-world events**, including the oscillatory events of 2016, 2017, and 2025, as well as under ambient conditions, ensuring that they do not generate false alarms.
- They are capable of computing **frequency**, **damping**, **mode shapes**, and energy for **triggering** purposes.
- All proposed approaches are sufficiently **fast** for real-time implementation.
- They perform effectively even with **limited datasets**, such as MedFasee dataset.

References

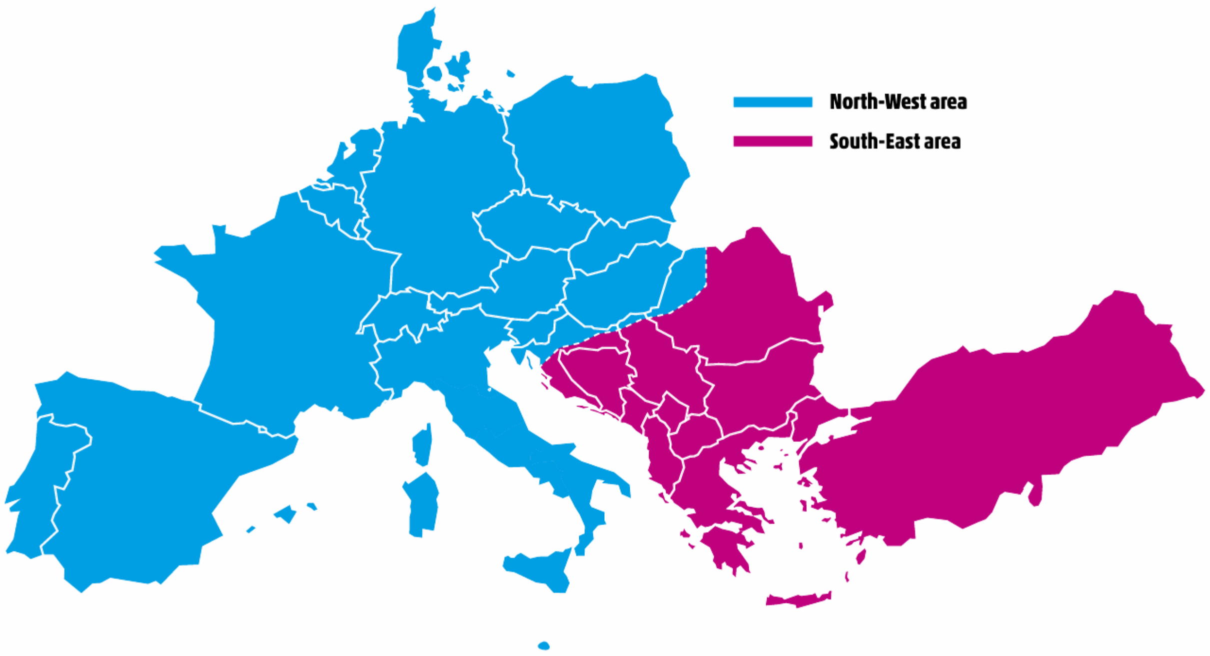
1. Berizzi, A., Bosisio, A., Simone, R., Vicario, A., Giannuzzi, G., Pisani, C., & Zaottini, R. (2020). Real-time identification of electromechanical oscillations through dynamic mode decomposition. *IET Generation, Transmission & Distribution*, *14*(19), 3992-3999.
2. Vicario, A., Berizzi, A., Giannuzzi, G. M., & Pisani, C. (2022). Practical implementation and operational experience of dynamic mode decomposition in wide-area monitoring systems of Italian power system. *Journal of Modern Power Systems and Clean Energy*, *11*(3), 793-802.
3. Bosisio, A., Berizzi, A., Moraes, G. R., Nebuloni, R., Giannuzzi, G., Zaottini, R., & Maiolini, C. (2019, July). Combined use of PCA and Prony analysis for electromechanical oscillation identification. In *2019 international conference on clean electrical power (ICCEP)* (pp. 62-70). IEEE.
4. Roy, R., Paulraj, A., & Kailath, T. (1986, October). Estimation of signal parameters via rotational invariance techniques-ESPRIT. In *MILCOM 1986-IEEE Military Communications Conference: Communications-Computers: Teamed for the 90's* (Vol. 3, pp. 41-6). IEEE.
5. Tufts, D. W., & Kumaresan, R. (2005). Estimation of frequencies of multiple sinusoids: Making linear prediction perform like maximum likelihood. *Proceedings of the IEEE*, *70*(9), 975-989
6. Brincker, R., & Andersen, P. (2006). Understanding stochastic subspace identification. In *Conference Proceedings: IMAC-XXIV: A Conference & Exposition on Structural Dynamics*. Society for Experimental Mechanics.

Real-Time Detection of Islanding Events via Low-Rank Subspace Clustering

02

Motivation

- One of the main stability concerns faced by TSOs is the occurrence of system **islanding**, where a portion of the power grid becomes electrically isolated from the rest of the network.
- Uncontrolled islanding occurs due to disturbances and does not align with the utility's operational strategy. Such unintentional separation can cause significant frequency and angle deviations within the isolated region, depending on local power imbalances and system inertia. If not properly managed, these deviations may **compromise the stability** of the islanded system.
- In this work, the core idea is to form **coherent clusters** from PMU measurements and, by analyzing their **mutual Euclidean distances**, distinguish between different dynamic phenomena. This clustering-based approach enables the detection of network islanding events as well as naturally occurring electromechanical oscillations within the interconnected power grid.



Theory

2.1

Clustering in the low-rank subspace

Model Order Reduction techniques, particularly Principal Component Analysis [1], are employed to project high-dimensional measurement data onto a lower-dimensional eigenspace, where hidden structure can be easily identified.

$$X = \begin{bmatrix} x_{1,t_1} & \cdots & x_{1,t_k} \\ \vdots & \ddots & \vdots \\ x_{N,t_1} & \cdots & x_{N,t_k} \end{bmatrix}$$

$$\Sigma W = \Lambda W$$

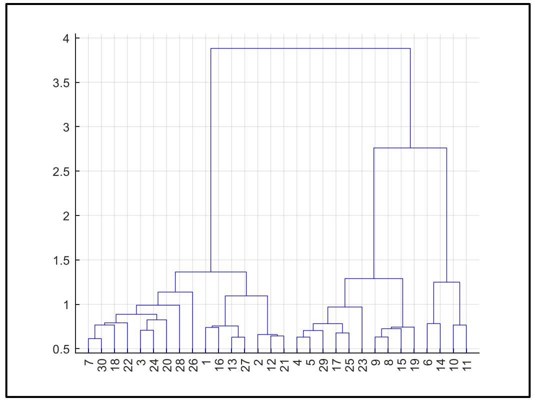
$$W_m = \begin{bmatrix} \vdots & & \vdots \\ v_1 & \dots & v_m \\ \vdots & & \vdots \end{bmatrix}$$

$$Y = XW_m$$

MOR

Within this reduced space, **Hierarchical Agglomerative Clustering** is applied to identify groups of coherent PMU signals[2]. HAC is a machine learning and data analysis method that incrementally merges similar elements into increasingly larger clusters[3].

$$\Delta(A,B) = \sum_{i \in A\cup B} ||\overline{x}_i - \overline{m}_{A\cup B}||^2 - \sum_{i\in A} ||\overline{x}_i - \overline{m}_A||^2 - \sum_{i \in B} ||\overline{x}_i - \overline{m}_B||^2$$



HAC

Mutual Euclidean distances and the **global silhouette index** [4] are employed as metrics to distinguish between different dynamic phenomena.

$$S_i = \frac{b(i) - a(i)}{\max(a(i), b(i))}$$

$$\mu_i = \frac{1}{|C_i|} \sum_{y_j \in C_i} y_j$$

$$D_{i,j} = \left|\left|\mu_i - \mu_j\right|\right|_2$$

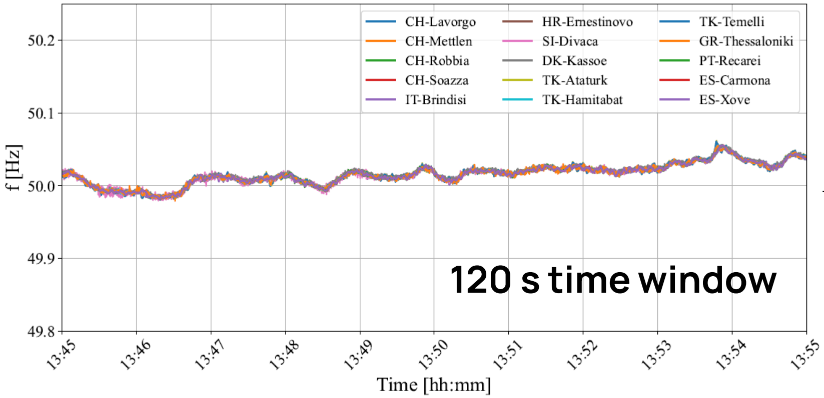
$$MED = \max\{D_{i,j}\}$$

Metrics

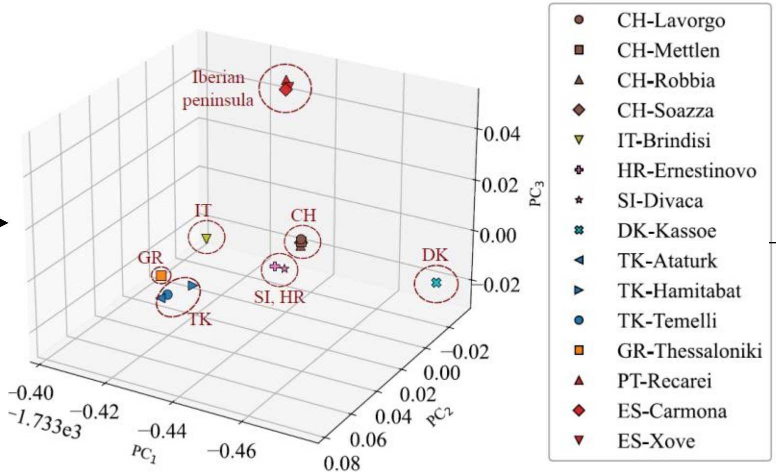
Applications

2.2

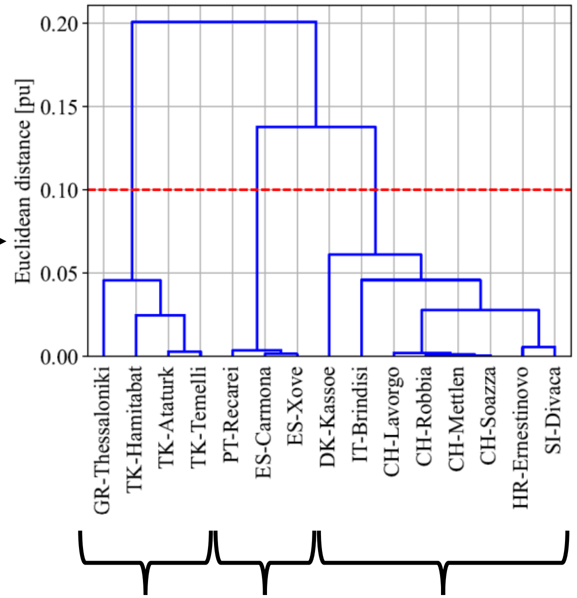
Normal grid operation in 2021



Low-rank subspace



HAC in $\mathbb{R}^3$



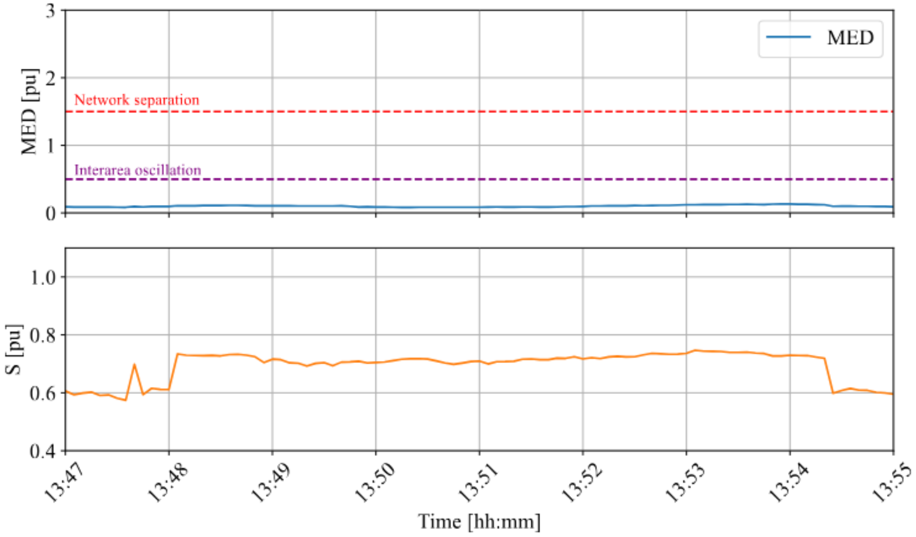
- Balkan area
- Iberian Peninsula
- CE

3 clusters

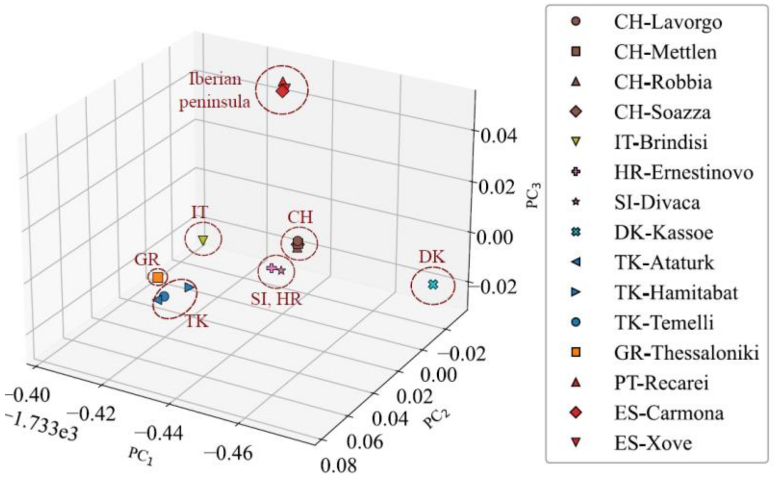
$S_g = 0.718$

$MED = 0.096$

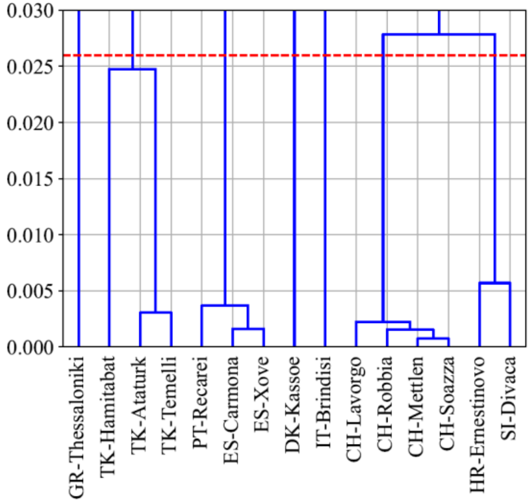
Using a moving time window:
MED $\simeq \mathbf{0}$
$\boldsymbol{S_g \simeq 0.6 \div 0.7}$

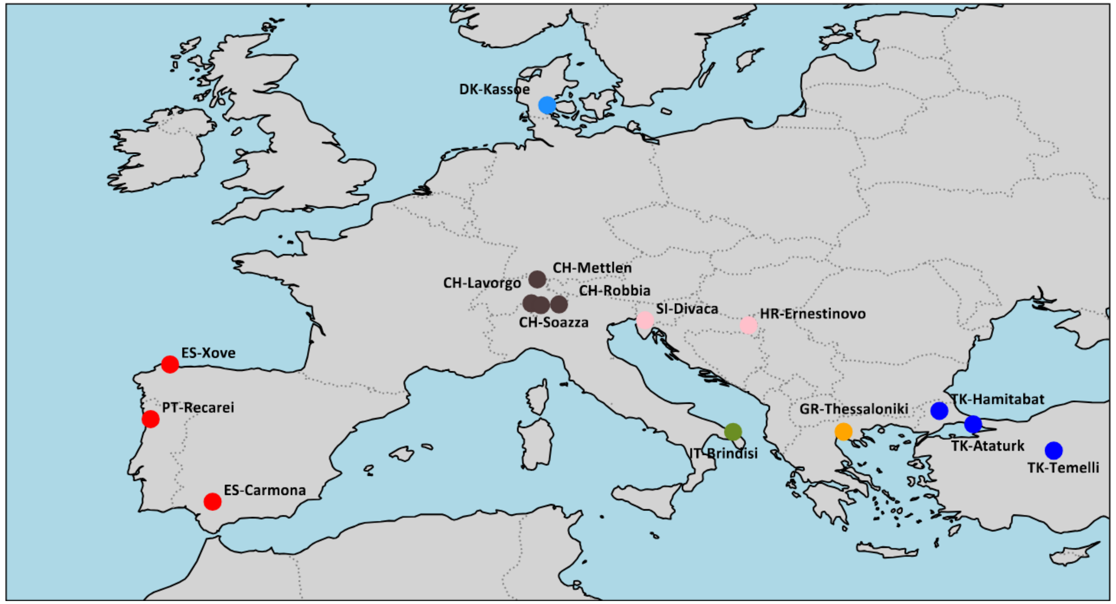


Normal grid operation in 2021 – coherent areas



Selecting 7 clusters



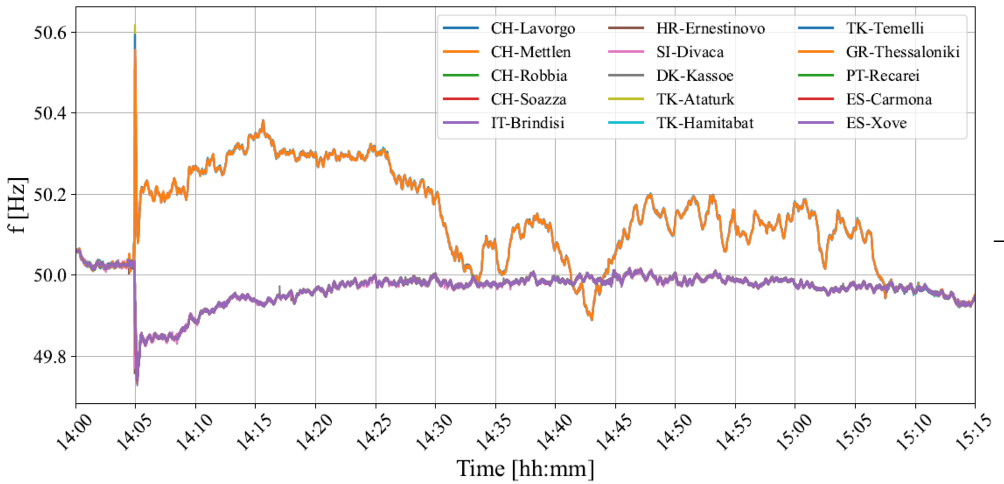


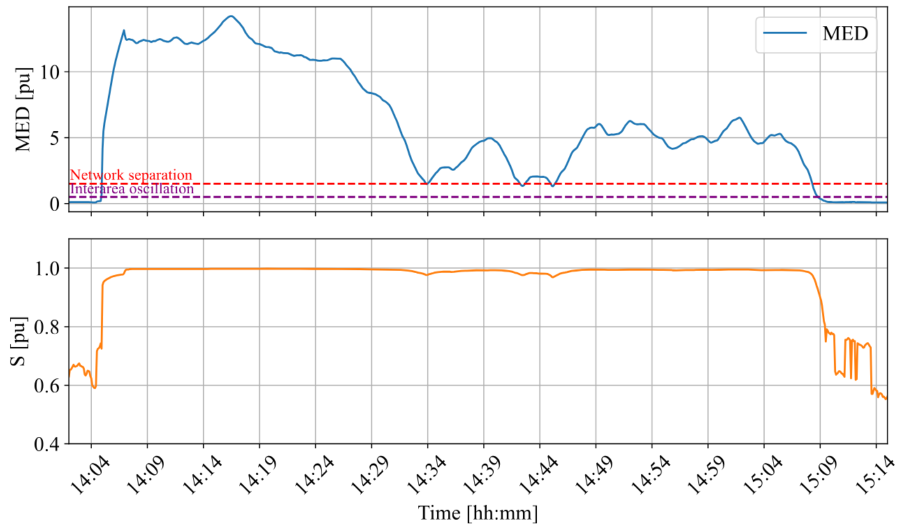
Even without incorporating any geographic information, the proposed method is able to ***group PMUs consistently with their geographical locations*** *by relying solely on ambient condition data.*

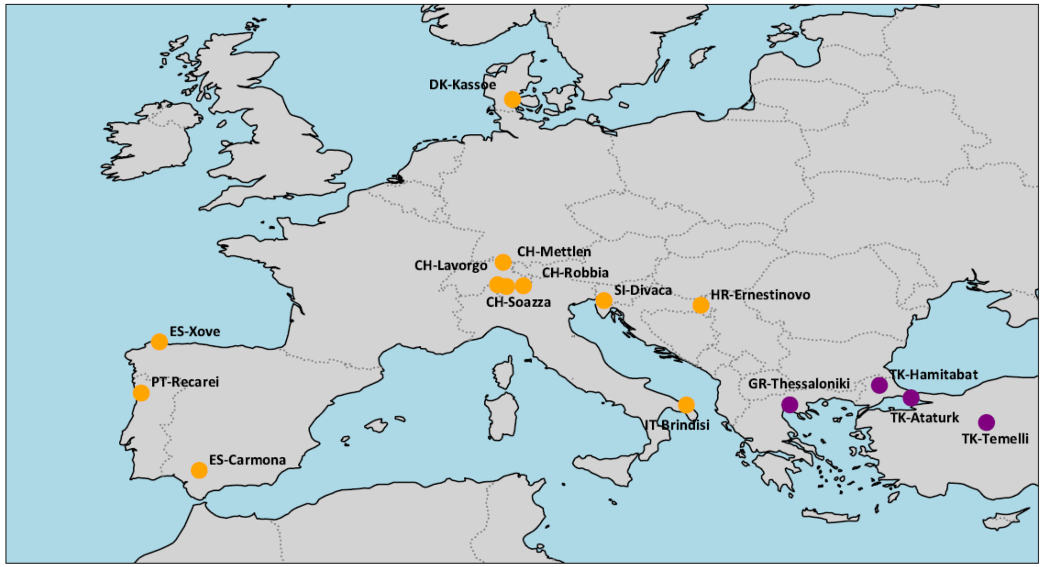
7 clusters

$S_g = 0.630$

Continental Europe Synchronous Area Separation on January 08th, 2021







ENTSO-E report:

12:04:54.56

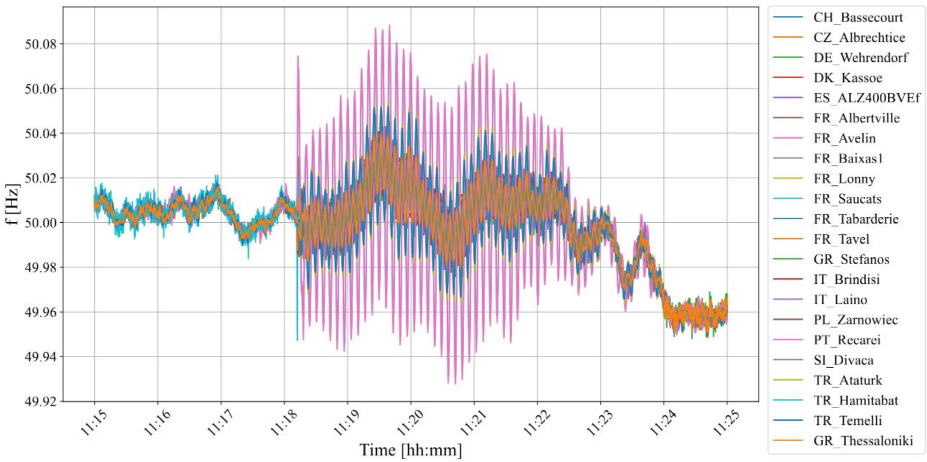
Proposed approach:

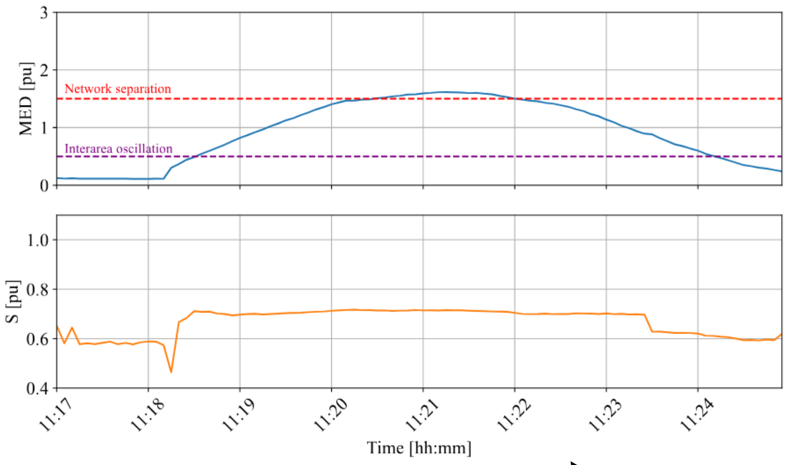
12:04:56.00

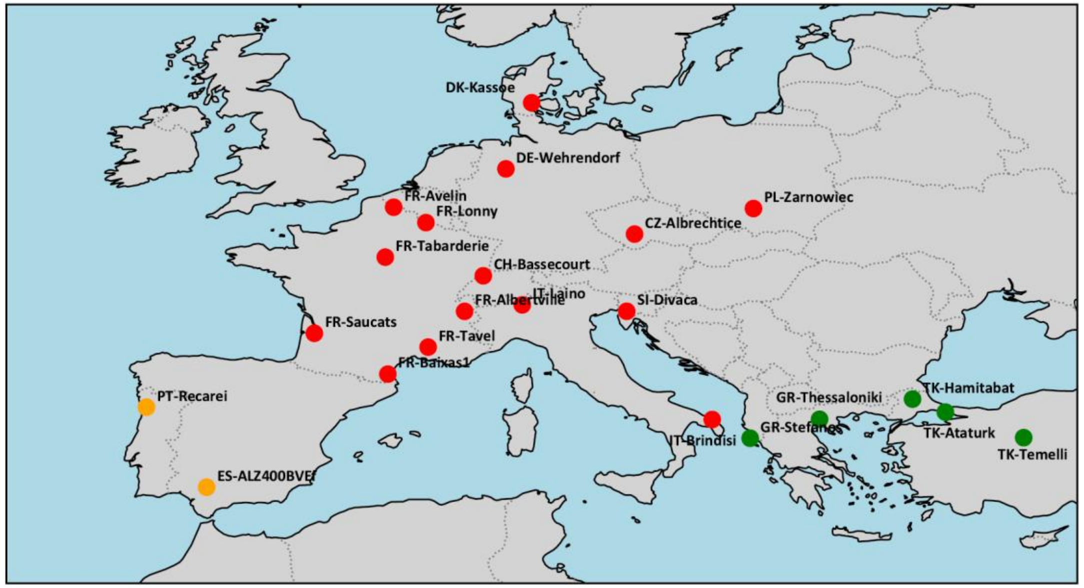
$MED \gg 1.5$

$S_g \simeq 1$

Oscillatory event in the European power system on December 1st, 2016







$MED \simeq 1.5$
$S_g \simeq 0.6 \div 0.7$

Iberian Power System Blackout on April 28th, 2025

- Analysis based on measurements from the **MedFasee** project, low-voltage WAMS

ENTSO-E report:

12:33:21

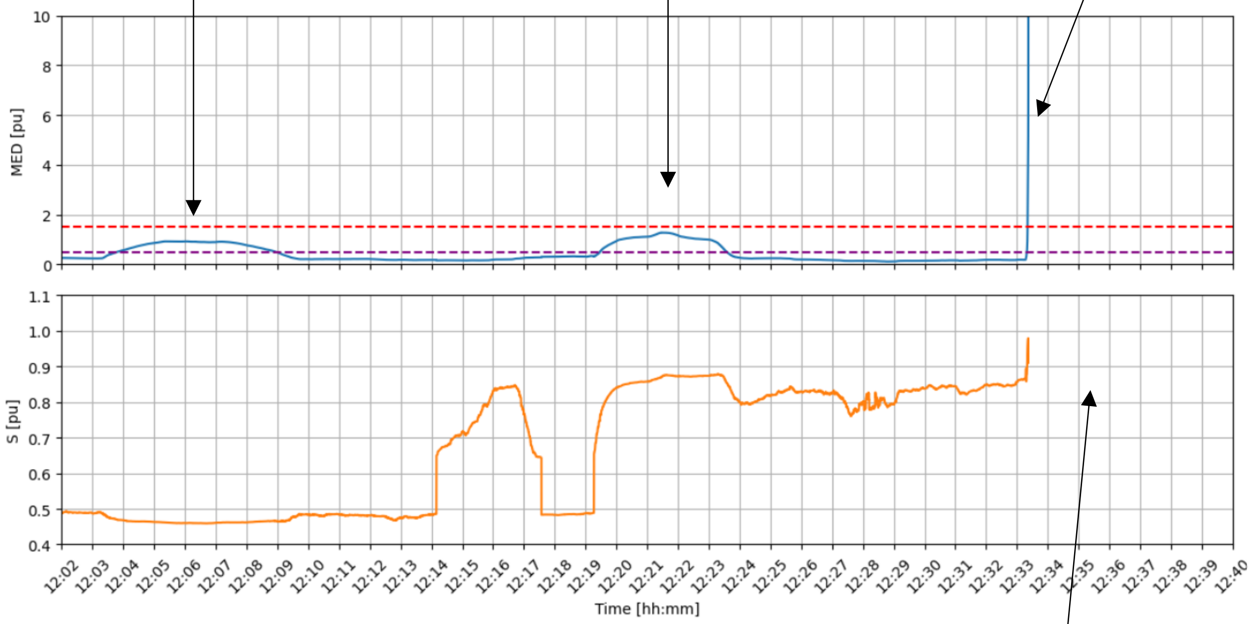
Proposed approach:

12:33:20.70

First oscillatory event

Second oscillatory event

Separation



Computation was halted following the blackout, as two of the three PMUs were out of service.

Conclusion

- The proposed approach employs **low-rank subspace** projection and **clustering** to group PMU measurements.
- **MED** and $\boldsymbol{S_g}$ are used to identify different possible scenarios within the power system, such as **ambient conditions**, **electromechanical oscillations**, or **network separations**.
- **MED** provides a measure of distance between clusters, while $\boldsymbol{S_g}$ evaluates the quality of clustering.
- The algorithm has been tested on various scenarios, including the **2021 CE SA separation**, the **2016 oscillatory event**, **ambient conditions**, and the **2025 Iberian power system blackout**. It performed well across all scenarios, enabling operators to quickly understand the type of event affecting the power system.
- Furthermore, the proposed approach proves highly effective in identifying **coherent areas** under ambient conditions, i.e., during normal frequency fluctuations.
- Lastly, a similar approach was proposed in [2] to group power system buses based solely on **voltage** measurements, and it was shown to be effective.

References

1. Abdi, H., & Williams, L. J. (2010). Principal component analysis. *Wiley interdisciplinary reviews: computational statistics*, *2*(4), 433-459.
2. Shirvani, R., Bosisio, A., Pomarico, A., Berizzi, A., Mosca, C., Cuccia, P., & Tisti, P. (2025). A data-driven approach for clustering extra high voltage buses: A case study on the Italian transmission network. *Sustainable Energy, Grids and Networks*, 101847.
3. Sharma, S., & Batra, N. (2019, February). Comparative study of single linkage, complete linkage, and ward method of agglomerative clustering. In *2019 international conference on machine learning, big data, cloud and parallel computing (COMITCon)* (pp. 568-573). IEEE.
4. Starczewski, A., & Krzyżak, A. (2015, June). Performance evaluation of the silhouette index. In *International conference on artificial intelligence and soft computing* (pp. 49-58). Cham: Springer International Publishing.

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