High Reporting Rate Measurements for Smart[er] Grids

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DL lecture from IEEE IMS

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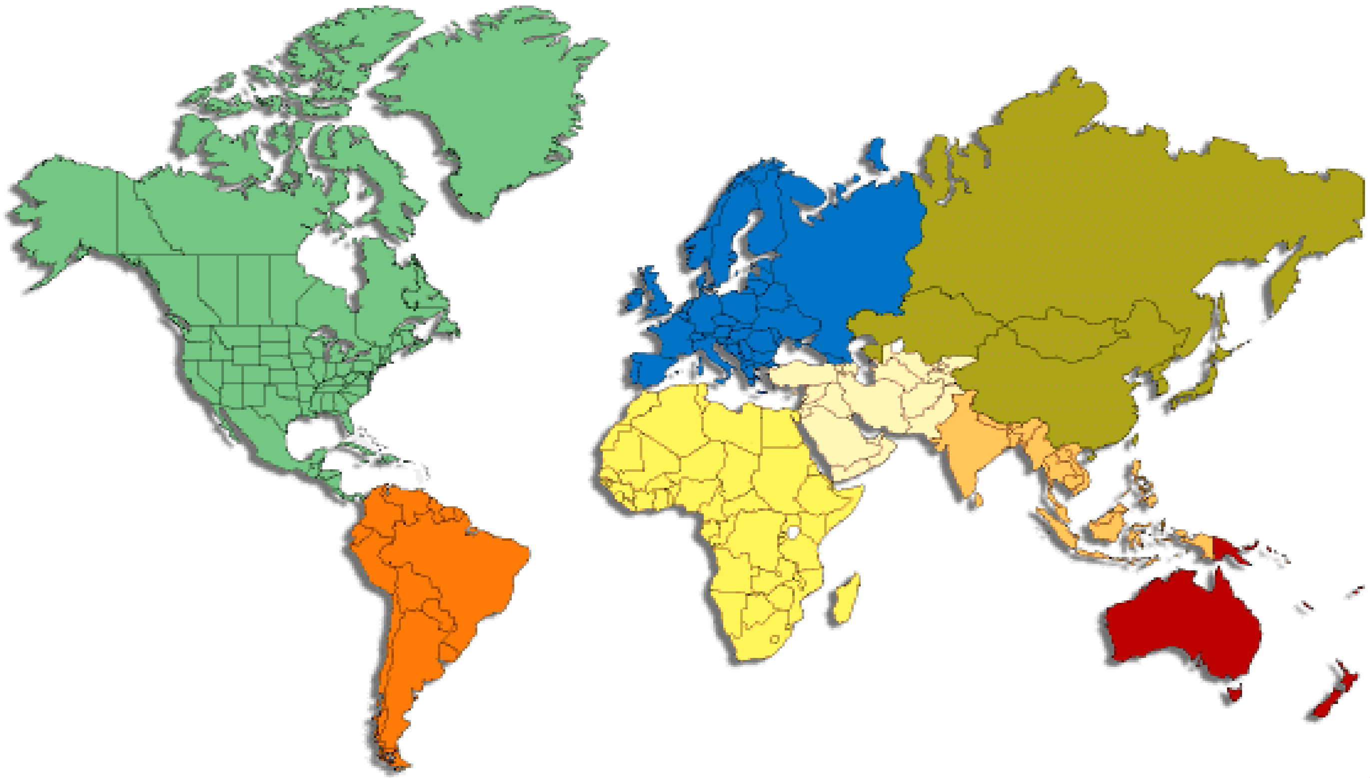
CHAPTERS

Region	Chapter s
1-6	8
7	6
8	14
9	4+2+2
10	23
Total	55



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CONFERENCES

IEEE International Workshop on Applied Measurements for Power Systems (AMPS)

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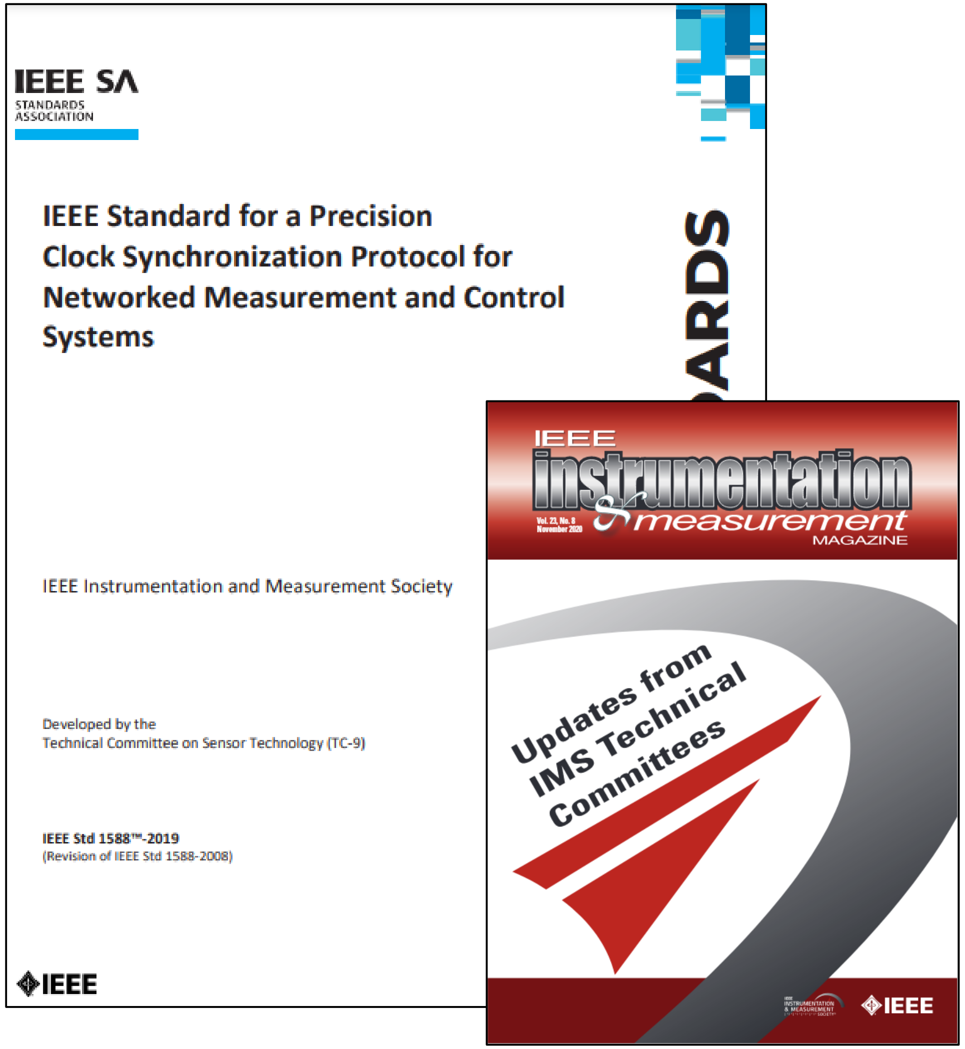

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National University of Science and Technology Politehnica Bucharest (UNSTPB)

- has its roots back to 1818
- 35000 students
- 15 faculties
- 2000 academic staff members
- 600 auxiliary staff members

MicroDERLab - Research and Innovation Projects

NOVETROL

NOVEL CURRENT CONTROL FOR CLIMATE NEUTRAL ENERGY INFRASTRUCTURE

CARDEA
Research Managers open Research Doors

Career Acknowledgement for Research (Managers) Delivering for the European Area

INFUSE
Information Fusion of Multi-Vector Real-Time Data Streams for Energy Management in Emerging Power Grids

Information Fusion of Multi-Vector Real-Time Data Streams for Energy Management in Emerging Power Grids

ECom4Future
Fiware Driven ENERGY COMmunities for the FUTURE

FIWARE DRIVEN ENERGY COMMUNITIES FOR THE FUTURE

eclipse

ENERGY CONSUMPTION REDUCTION BASED ON OPEN-SOURCE REFERENCE FRAMEWORK

I-GRETA
Intelligent FIWARE-based generic energy storage services for environmentally responsible communities and cities.

DC NEXT EvE

FI SMEP

FIWARE for Smart Energy Platform

DCNextEvE a H2020 –MSCA (2016-2018) project (Fellow dr. Irina Ciornei) with the main purpose to design and analysis of novel methods for management and control of multiple building scale DC microgrids

EMERGE
Advanced Measurement Framework for Emerging Electric Power Systems

An ICT platform for Sustainable Energy Ecosystem in Smart Cities

ITCity

STORAGE4GRID

Nobel Grid
Smart energy for people

Flexible Smart Metering for Multiple Energy Vectors with active Prosumers

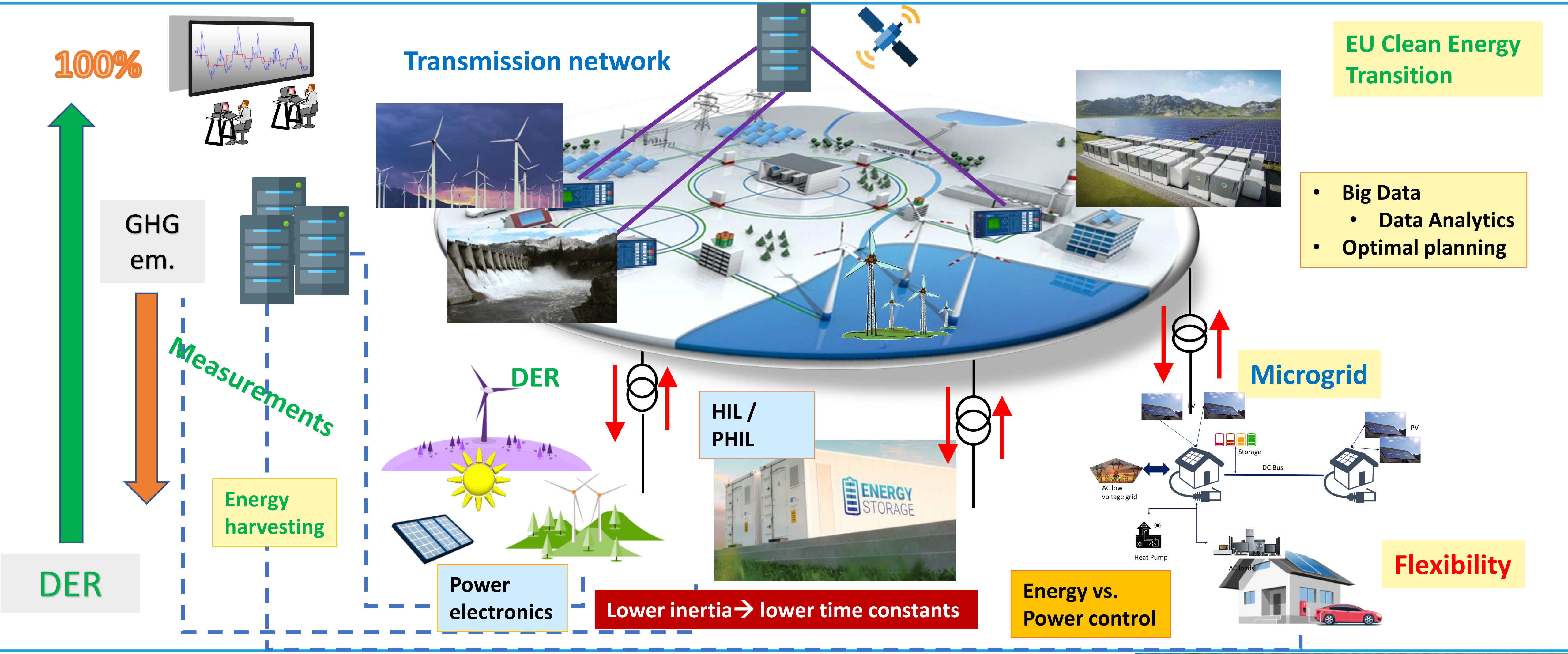
FLEXMETER

New cost-efficient models for flexible Smart grids

OUTLINE

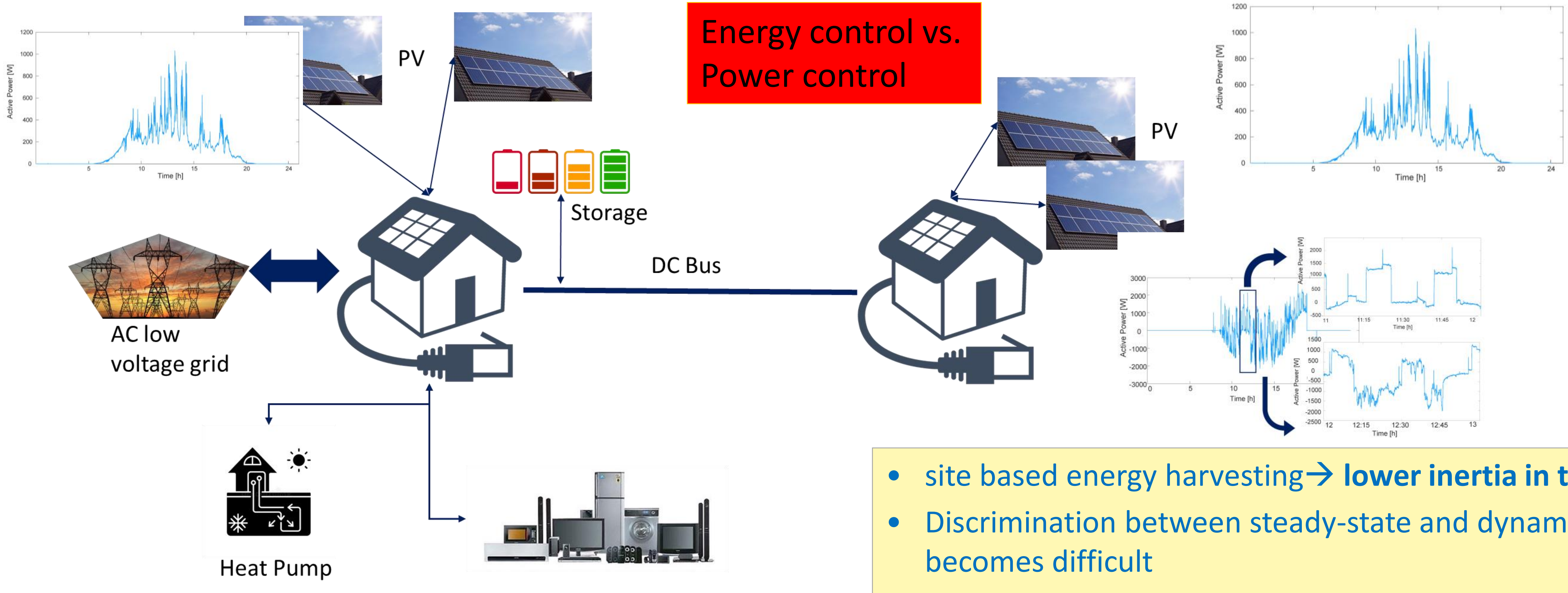
- EMERGING POWER SYSTEMS REQUIRE NEW PARADIGM FOR CONTROL
- MEASUREMENT PARADIGM IN POWER SYSTEMS: LOSSY COMPRESSION
- MEASURES FOR VARIABILITY. INFORMATION LOSS. **GOODNESS OF FIT**
- HIGH REPORTING RATE MEASUREMENTS
- APPLICATIONS: POWER PROFILES, FREQUENCY, NET POWER FLOW VARIABILITY
- ELEMENTS OF **DATA ANALYTICS** AND FORECASTING BASED ON **OUTLIERS FILTERING** (AS A FUNCTION OF VARIABILITY)

[Emerging] Power Systems



Game changers. Non-controllable, intermittent generation. Static conversion. DC grids.

Energy control vs. Power control

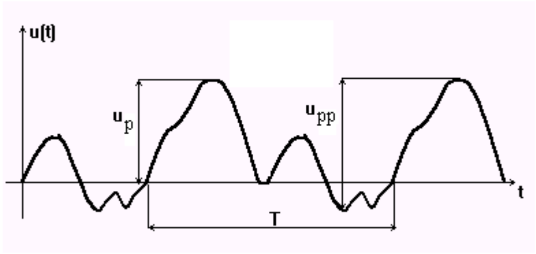


- office appliances: **DC native loads** or DC compatible;
- Higher efficiency of the energy transfer at higher frequencies

- site based energy harvesting→ **lower inertia in the AC grids**
- Discrimination between steady-state and dynamic operation becomes difficult
- control ← real-time measurements & **accurate estimation of load flexibility**
- planning ← **accurate load/generation** profiles estimation

INFORMATION COMPRESSION

Periodic signals ar represented by only a few parameters **-> lossy information compression**



- Amplitude U, peak-to-peak value u_{pp}
- mean value: $$\bar{u} = \frac{1}{T}\cdot\int_{t_0}^{T+t_0} u(t)\,dt \qquad \bar{u}_k = \frac{1}{N}\times\sum_{j=k}^{j=N+k-1} u[j]$$
- average value: $$\overline{|u|} = \frac{1}{T}\cdot\int_{0}^{T} |u(t)|\,dt = \frac{2\cdot\hat{U}}{\pi}$$
- root mean square value; rms: $$U = \sqrt{\frac{1}{T}\cdot\int_{0}^{T}[u(t)]^2\,dt} = \frac{\hat{U}}{\sqrt{2}} \qquad U_k = \sqrt{\frac{1}{N}\times\sum_{j=k}^{j=N+k-1} u^2[j]}$$

The measurement paradigm in power systems: **[hidden!] data compression**

rms reported @ 3s:
1 min,
1 channel,
1 measurand: **40 Byte**

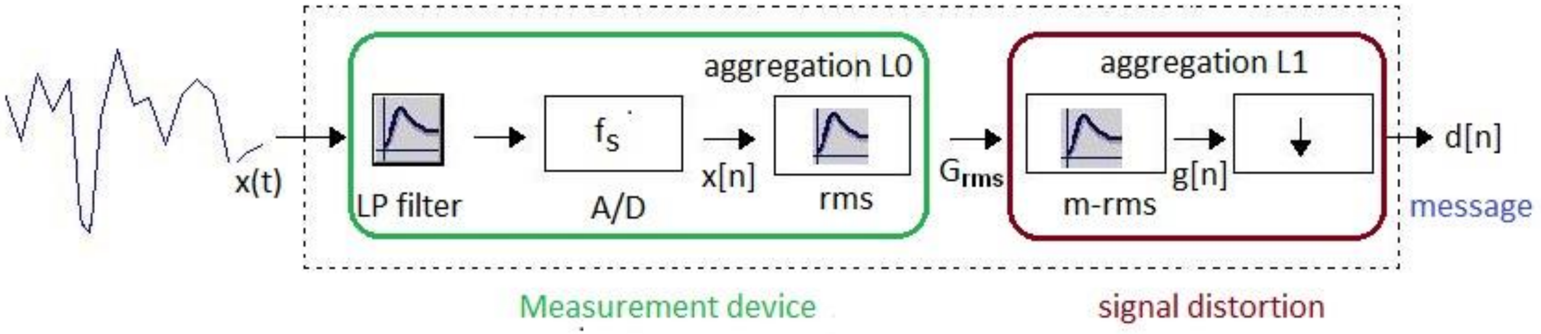
waveform, sampling @ 150 kHz
1 min,
1 channel,
1 measurand: **120 MB**

DATA AGGREGATION. FURTHER INFORMATION LOSS

- by averaging the measurement result, the message becomes **less sensitive to measurement errors**;
- However, there is a **lack of significance** of the quantity at the end of aggregation process:
- **the decimation introduces an additional uncertainty which is associated NOT with the measurement but with the meaning of the resulting quantity;**
- this error can be related to the "adequacy" of the information [output message] to the model (of the physical system) → **definitional uncertainty,** *an estimate of* **the semantic noise**

Measurement:
information **compression**
(and **coding**)

$$u = \sqrt{(u^*_M)^2 + (u^*_{RM})^2}; \qquad u^*_{RM} = \sqrt{\frac{u^2_{RM}}{N}}$$



u^*_M : model/definitional uncertainty

u_{RM} : uncertainty associated with the measurement value;

u^*_{RM}: uncertainty associated with the reported aggregated measurement value;

The Measurement Context in the Emerging Power Systems

Synchronized measurements

Lossy algorithms

power[s]

frequency

• rocof

phasor

advanced measurement systems (and data communication)

[still!] traditional/old/ models for the energy transfer

?

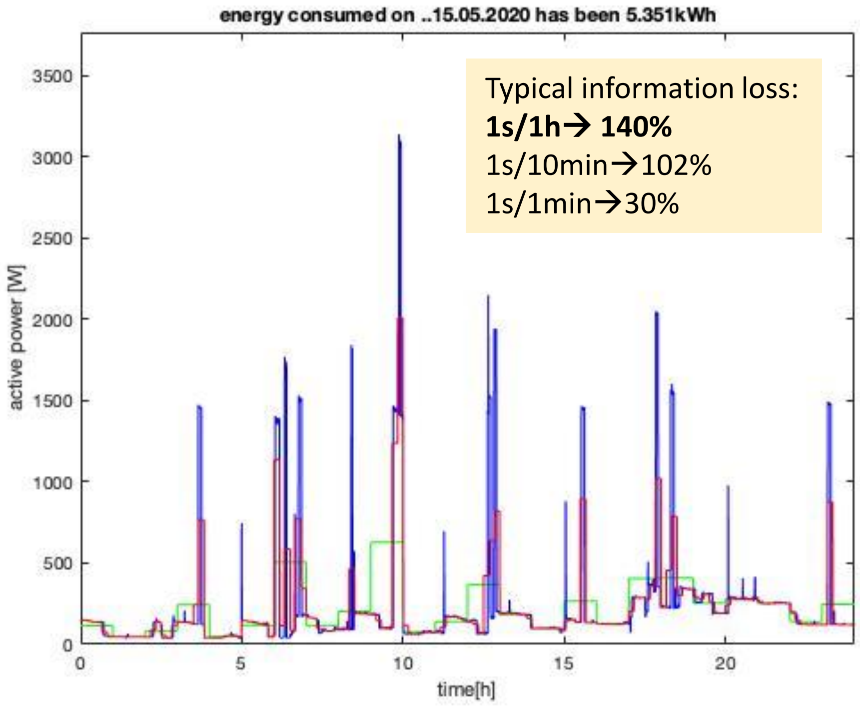
WAMCS

IoT

Unknown aggregation

Non optimal control of the energy transfer

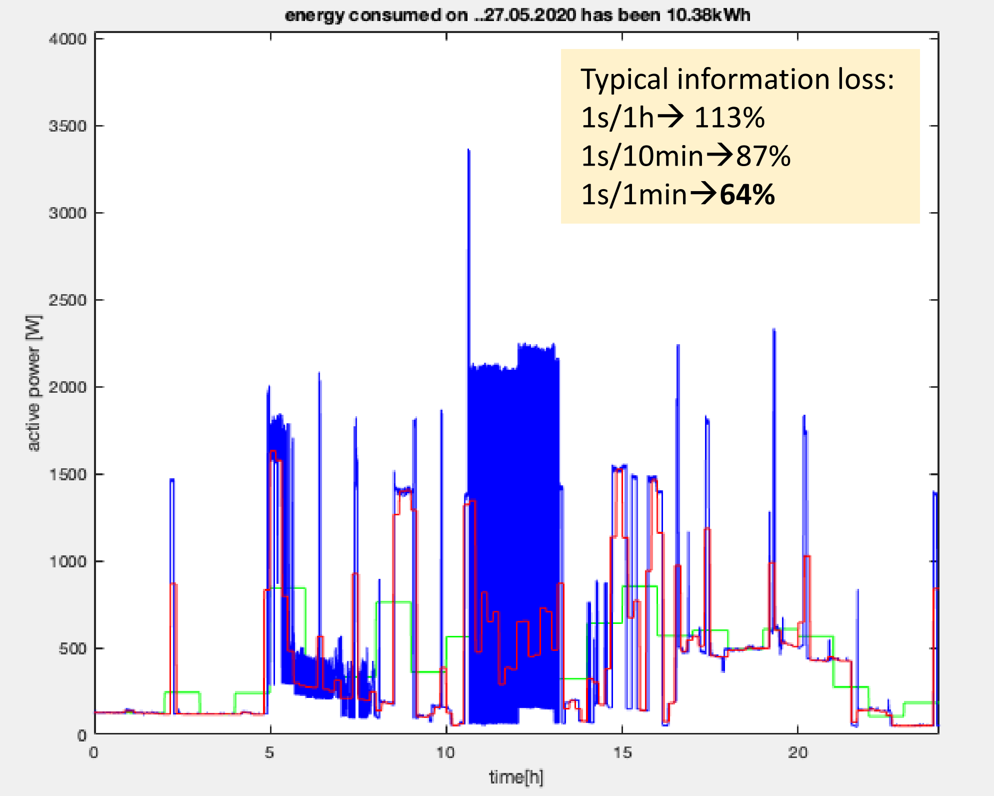
MEASUREMENTS AND INFORMATION. REPORTING /COMMUNICATION RATE



22MB/day, as .txt
1.2 MB/day as .zip

$$info\_loss_{interval} = \frac{std\_agg_{interval}}{P_{mean}^{1\ day}}$$

Radu Plămănescu, Mihai Valentin Olteanu, Viorel Petre, Ana-Maria Dumitrescu, Mihaela Albu, "Knowledge extraction from highly-variable power profiles in university campus", U.P.B. Sci. Bull., Series C, Vol. 84, Iss. 4, 2022

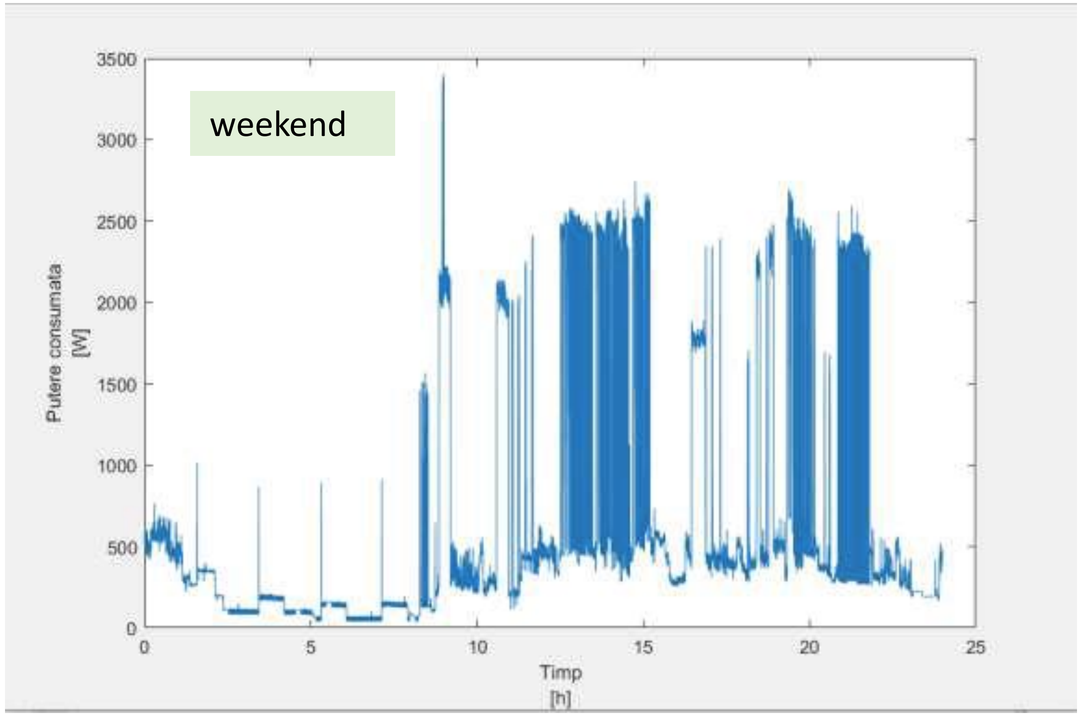


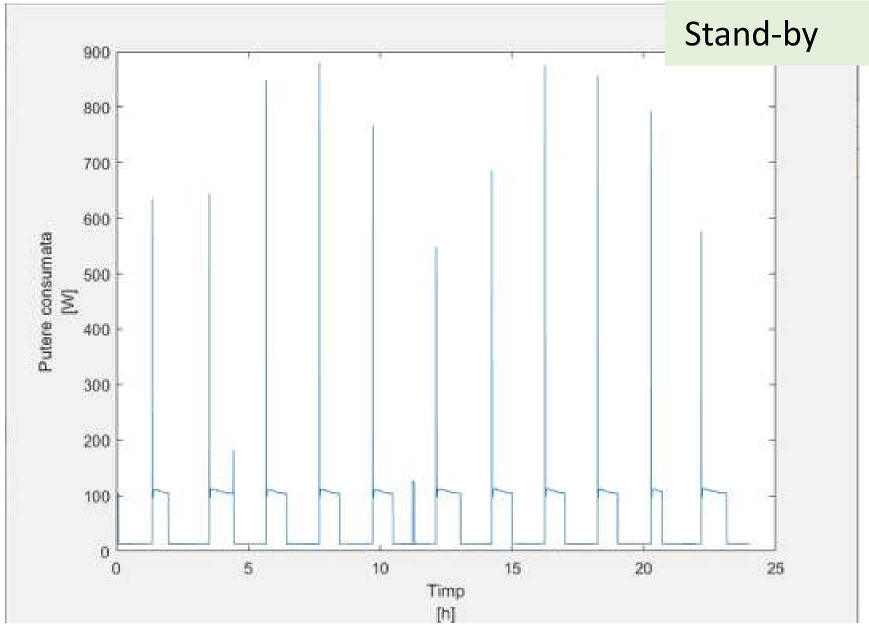
$$P_{mean}^{1\ day} = \frac{\sum_0^{N-1} P_i}{N}$$

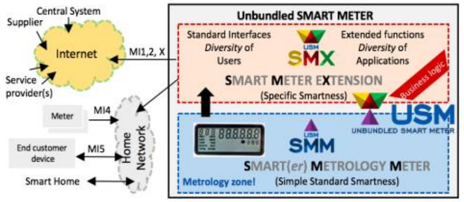
$$std\_agg_{interval} = \sqrt{\frac{\sum(P_x - \overline{P_{a,}})\hat{}2}{N}}$$

Grigore Stamatescu, Mihaela Albu, Mihai Sanduleac, "Residential Smart Meter Energy Time Series: Active power measurements with 1s reporting rate", IEEE Dataport, doi: https://dx.doi.org/10.21227/3yea-xm39.

EXAMPLES OF LOAD PROFILES







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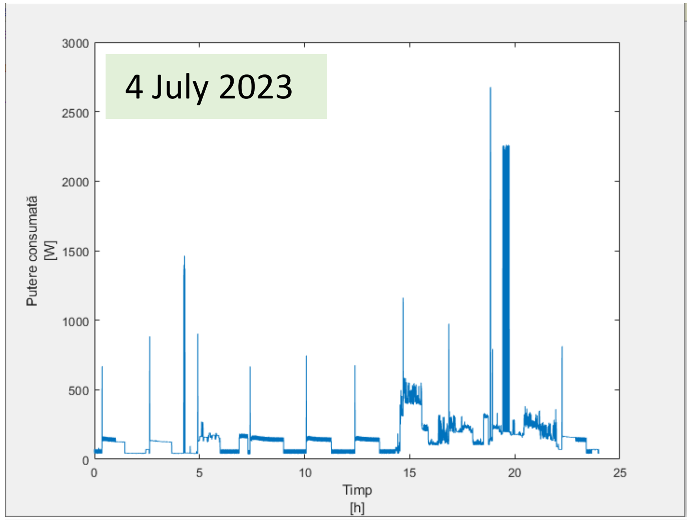
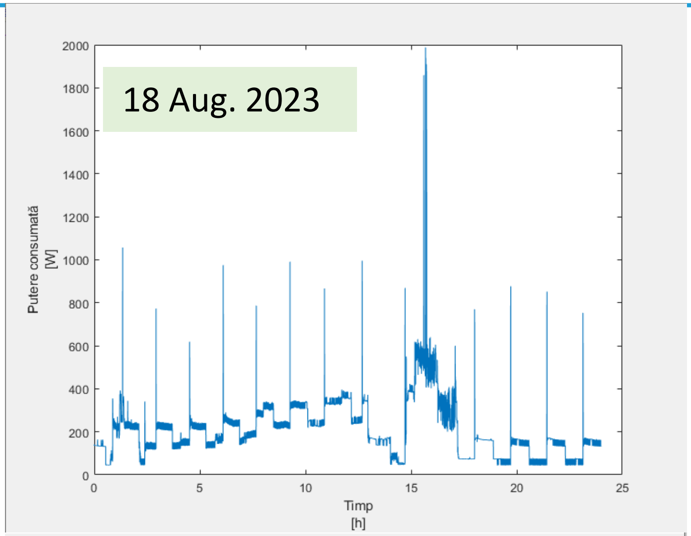
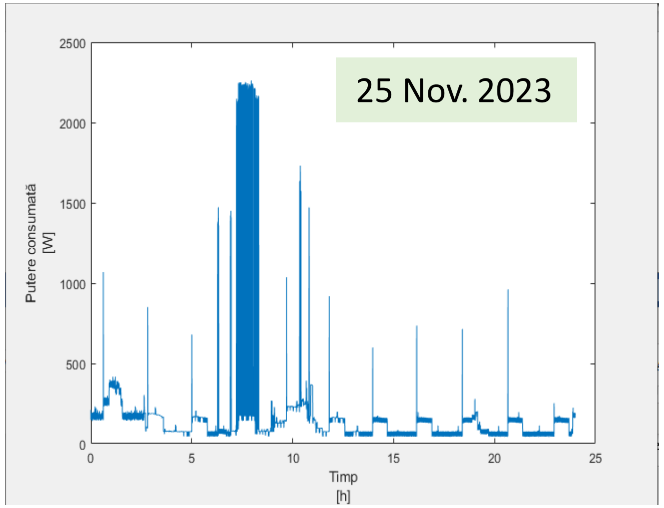
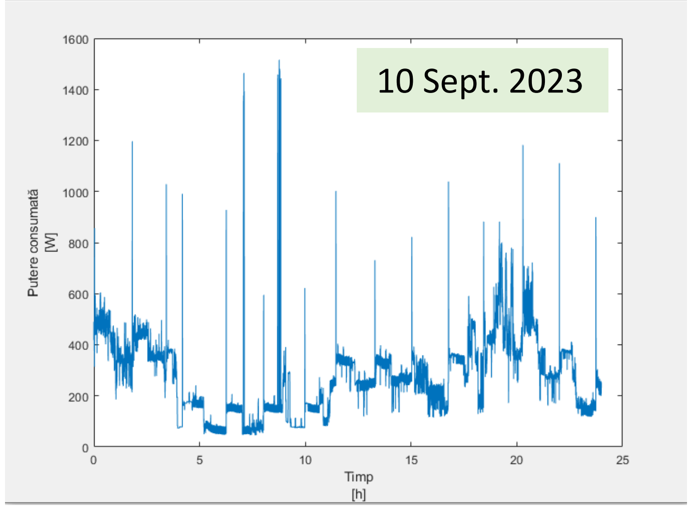
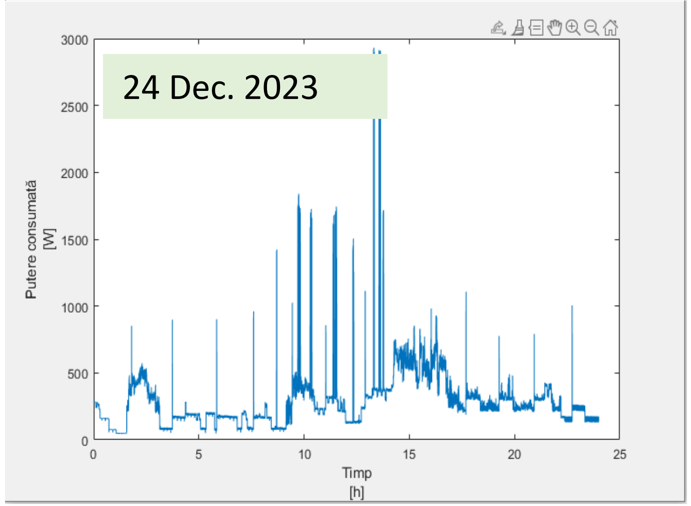
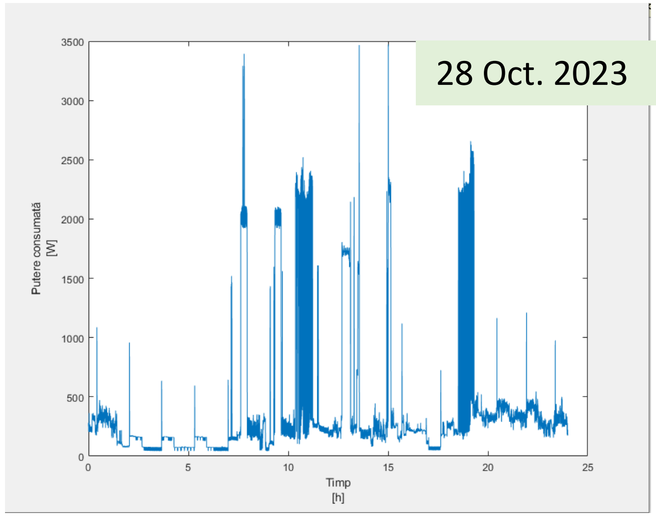












IEEE INSTRUMENTATION & MEASUREMENT SOCIETY®

METRICS FOR SIGNAL VARIABILITY ASSESSMENT AGAINST A CHOSEN MODEL

$$MAE = \frac{\sum_{i=1}^{n}|x_i - y_i|}{n} = \frac{\sum_{i=1}^{n}|e_i|}{n}$$

$$MSE = \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} = \sqrt{MSE}$$

$$CV(RMSE) = \frac{1}{\bar{y}}\sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{x_i - y_i}{x_i}\right|$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

$$MASE = \frac{MAE}{\frac{1}{n-1}\sum_{i=1}^{n}|x_i - y_p|}$$

$$MSPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{x_i - y_i}{x_i}\right|^2$$

$$x_i = P_i;\ y_i = \bar{y} = \frac{\sum_{i=1}^{N_r} P_i}{N_r};\ \tilde{y}_i = \frac{\sum_{i=1}^{N_{ss}} P_i}{N_{ss}} = \tilde{y}$$

y_i – estimate/**model** value

x_i – measured value,

N – number of measured values available during the analysis window T_w

The coefficient of variation of RMSE - **CV(RMSE)** normalizes the root mean squared error value using the model value. The coefficient of determination R^2 is a metric used to assess the predictive capability of a linear regression model. It indicates the normalized measure **of how well the model fits the data.**

Measurement. Information Loss. How to estimate it?

The **identification process** for the **parameters** that characterize a **deterministic signal** is equivalent to a matching mathematical problem also known in the statistic science field as the goodness of fit.

Goodness-of-fit: a statistical test that determines **how well a system fits a set of observations**. The metrics are usually calculated based on the differences between **the observed and the expected values according to the model.**

$$GoF = 20lg \frac{\hat{X}}{\sqrt{\frac{1}{(n-m)} \sum_{i=1}^{n} (x_i - y_i)^2}}$$

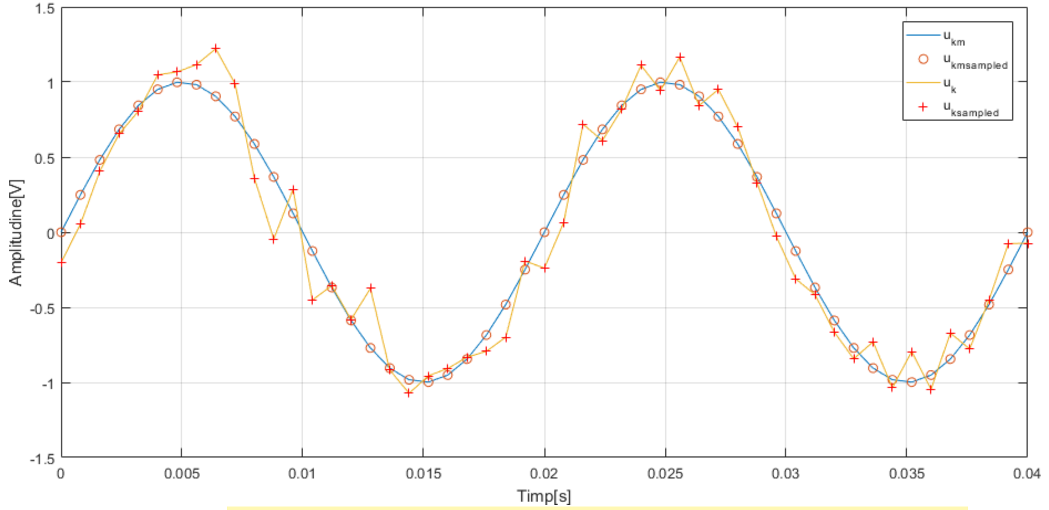
$$MAE = \frac{\sum_{i=1}^{n} |x_i - y_i|}{n}$$

$$MSE = \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}} = \sqrt{MSE}$$

$$CV(RMSE) = \frac{1}{\bar{y}} \sqrt{\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

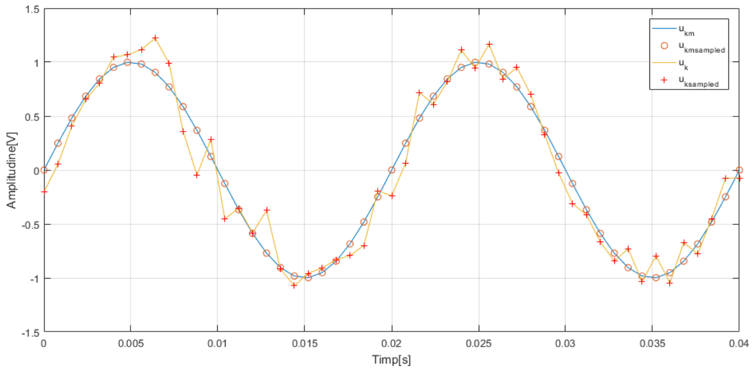


N_{w1}=128; N_{w2}=1024; T_w=10 min

Harold Kirkham , Artis Riepnieks,– "Dealing with Non-Stationary Signals: Definitions, Considerations and Practical Implications", IEEE PES GM 2016.

G4500 BlackBox (Elspec)

Measurement Definitial Uncertainty and The Ideal Waveform Model



N_{w1}=128; N_{w2}=1024; T_w=10 min

$$CV(RMSE) = \frac{1}{\bar{y}}\sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Anca BRINCOVEANU, E. FIORENTIS, R. PLAMANESCU, Ana-Maria DUMITRESCU, Mihaela ALBU, *Signal Model Adequacy Indicator for Power Quality Monitoring*, International Workshop of Electromagnetic Compatibility, CEM-2022, Suceava, Sept. 2022

Metrics N_{w1}=128;	Values for phase 1	Values for phase 2	Values for phase 3	Reference value
MAE[V]	25.493	5.671	5.467	0
MSE[V^2]	853.452	40.162	44.347	0

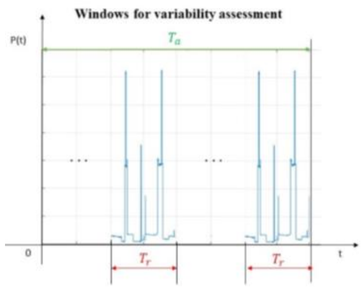
Metrics N_{w2}=1024	Values for phase 1	Values for phase 2	Values for phase 3	Reference value
MAE[V]	8.255	7.663	67.824	0
MSE[V^2]	91.371	80.094	5840	0
RMSE[V]	9.558	8.949	76.419	0
CV(RMSE) [V]	0.043	0.0378	0.345	0
R^2[V]	0.988	0.994	0.998	1

Metrics for Power Profile variability – Low Reporting Rates

$$CV(RMSE) = \frac{1}{\bar{y}}\sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

$$x_i = P_i;\ y_i = \bar{y} = \frac{\sum_{i=1}^{N_r} P_i}{N_r};\ \tilde{y}_i = \frac{\sum_{i=1}^{N_{ss}} P_i}{N_{ss}} = \tilde{y}$$



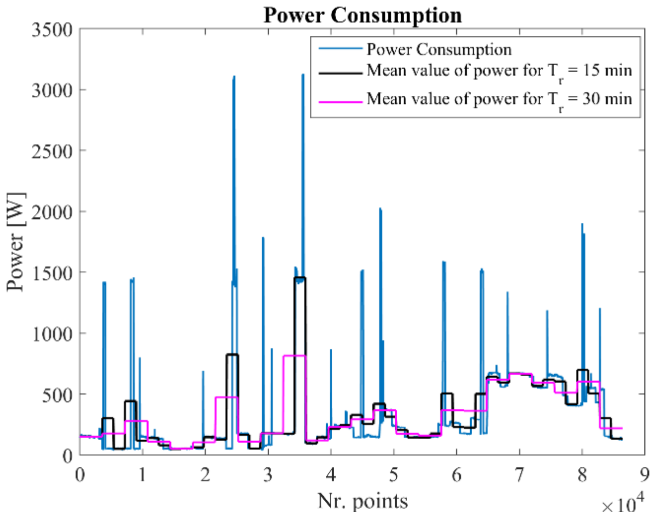
$$GoF = 20lg\frac{\hat{X}}{\sqrt{\frac{1}{(n-m)}\sum_{i=1}^{n}(x_i - y_i)^2}}$$

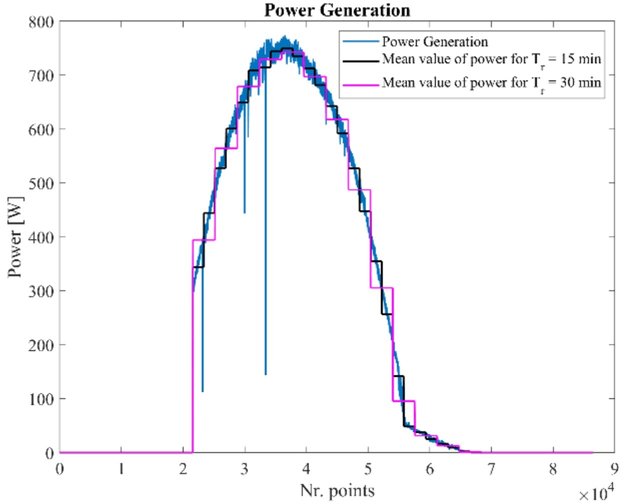
y_i – **model value** x_i – measured value,

n – number of measured values available during the analysis window T_r

m - number of parameters estimated in the equation; $(n–m)$ is the residual degrees of freedom ; $\hat{X}$ is the signal amplitude

METRICS FOR POWER PROFILE VARIABILITY – EXAMPLE OF A HOUSEHOLD POWER PROFILE AND PV





Metrics for active power profile for T_r= 15 minutes

NR.	TIME	MAE	MSE	RMSE	CV(RMSE)	MAPE	MSPE	R^2	MASE
T_{r1}	00:15	5.09E+00	3.49E+01	5.91E+00	2.62E-02	1.23E-03	1.59E-06	-1.21E+01	3.11E+00
T_{r2}	00:30	3.20E+00	2.02E+01	4.49E+00	1.99E-02	1.35E-03	6.55E-07	-6.56E+00	1.96E+00
T_{r3}	00:45	2.13E+01	1.07E+03	3.26E+01	1.45E-01	5.41E-02	6.05E-05	-3.99E+02	2.21E+00
T_{r4}	01:00	6.31E+02	4.26E+05	6.53E+02	2.90E+00	1.94E-01	2.30E-02	-6.90E+00	1.36E+00
T_{r5}	01:15	4.80E+00	3.15E+01	5.62E+00	2.49E-02	3.74E-03	4.81E-06	-1.08E+01	2.94E+00
T_{r6}	01:30	3.15E+00	1.52E+01	3.90E+00	1.73E-02	2.34E-04	1.75E-06	-4.71E+00	1.93E+00
T_{r7}	01:45	4.35E+00	2.70E+01	5.19E+00	2.31E-02	8.17E-04	3.02E-06	-9.11E+00	2.66E+00
…		…	…	…	…	…	…	…	…
T_{r95}	23:45	3.36E+00	3.24E+01	5.69E+00	1.20E-02	3.96E-04	3.74E-07	-9.25E-01	8.19E-01
T_{r96}	24.00	2.39E+00	1.05E+01	3.25E+00	6.83E-03	4.00E-04	1.42E-07	3.75E-01	5.83E-01

Anca Petruta Brincoveanu, Radu Plămănescu, Ana-Maria Dumitrescu, Irina Ciornei – "Assessment of Power Profiles in LV distribution grids", The 8th Intern. Symposium on Electrical and Electronics Engineering, Galati, 26-28 Oct. 2023

Metrics for active power profile for T_r= 30 minutes

NR.	TIME	MAE	MSE	RMSE	CV(RMSE)	MAPE	MSPE	R^2	MASE
T_{r1}	00:30	4.84E+00	4.40E+01	6.63E+00	4.06E-02	1.98E-03	2.19E-04	-1.55E+01	2.95E+00
T_{r2}	01:00	1.20E+01	5.45E+02	2.33E+01	1.43E-01	5.33E-02	5.94E-05	-2.03E+02	2.13E+00
T_{r3}	01:30	4.09E+02	2.77E+05	5.26E+02	3.22E+00	1.15E-01	1.34E-02	-1.32E+01	1.76E+00
T_{r4}	02:00	3.87E+00	2.38E+01	4.88E+00	2.99E-02	3.80E-04	5.28E-06	-7.92E+00	2.37E+00
T_{r5}	02:30	5.59E+02	3.85E+05	6.20E+02	3.18E+00	3.84E-01	7.89E-02	-5.25E+00	1.59E+00
T_{r6}	03:00	4.29E+01	2.40E+03	4.90E+01	2.52E-01	5.30E-03	6.11E-04	-6.32E+02	1.87E+01
T_{r7}	03:30	6.37E+00	7.06E+01	8.40E+00	4.31E-02	1.45E-03	2.54E-06	-1.76E+01	3.24E+00
T_{r8}	04:00	3.72E+01	1.52E+03	3.90E+01	2.00E-01	1.38E-02	1.36E-04	-4.00E+02	1.91E+01
…		…	…	…	…	…	…	…	…
T_{r47}	23:30	1.84E+02	3.59E+04	1.90E+02	4.62E-01	1.62E-02	4.60E-04	-2.13E+03	3.52E+00
T_{r48}	24.00	5.63E+00	5.06E+01	7.12E+00	1.73E-02	9.99E-04	1.24E-06	-2.01E+00	1.37E+00

IEEE INSTRUMENTATION & MEASUREMENT SOCIETY

GoF FOR POWER PROFILE VARIABILITY

Define /select the model of the power profile

$P_i = 0,\ y_i = P_{max},\ (\forall)\ i = \overline{1,n},\ n = T_r/T_s$

$$GoF = 20lg \frac{P_{max}}{\sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n}(0 - P_{max})^2}} \rightarrow \mathbf{0}$$

P_i = constant = $P_n,\ y_i = P_{max},\ (\forall)\ i = \overline{1,n},\ n = T_r/T_s$.

$$GoF = 20lg \frac{P_{max}}{\sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n}(P_n - P_{max})^2}}$$

LV circuit with $P_n/P_{max} = 0.77$,
***GoF* is 12.73 dB**.

P_i -corresponds to a real power profile data, $P_i \leq P_n < P_{max}$,
$y_i = \frac{\sum_{i=1}^{n} P_i}{n} = \tilde{P} < P_{max},\ (\forall)\ i = \overline{1,n},\ n = T_r/T_s$

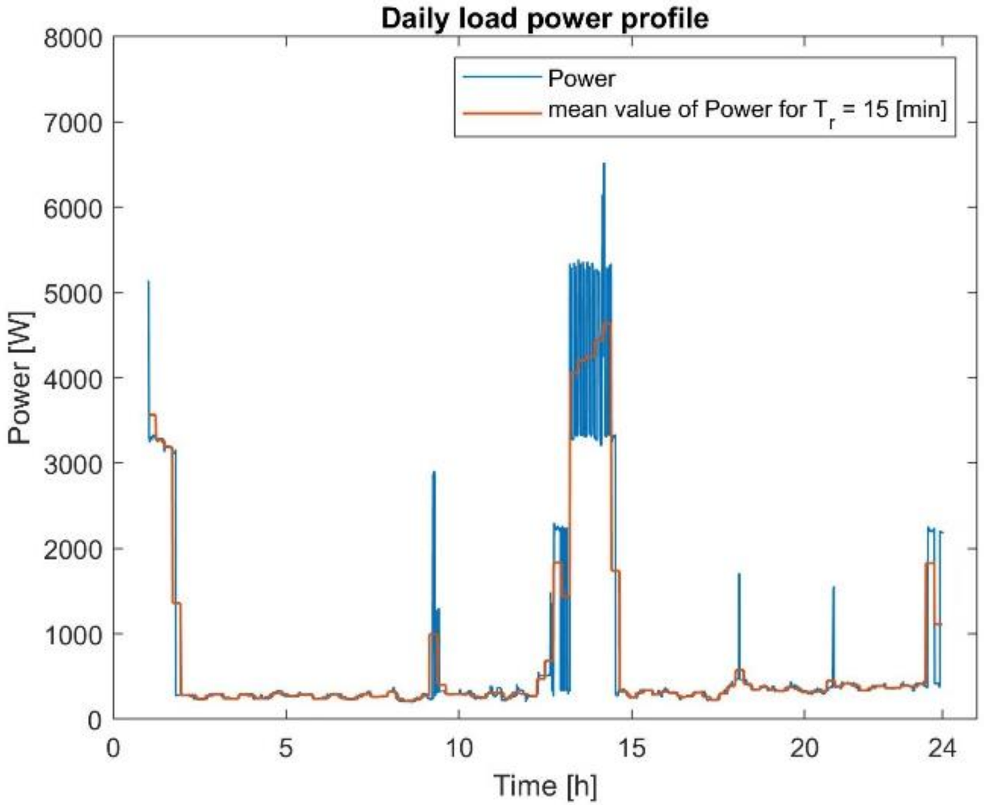
$$0 < GoF = 20lg \frac{P_{max}}{\sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n}(P_i - \tilde{P})^2}} = 20\ lg \frac{P_{max}}{std(P_i)}$$

P_i -corresponds to the real power profile obtain with a sampling rate f_s, $P_i \leq P_n < P_{max},\ y_i = P_{max},\ (\forall)\ i = \overline{1,n},\ n = T_r/T_s$.

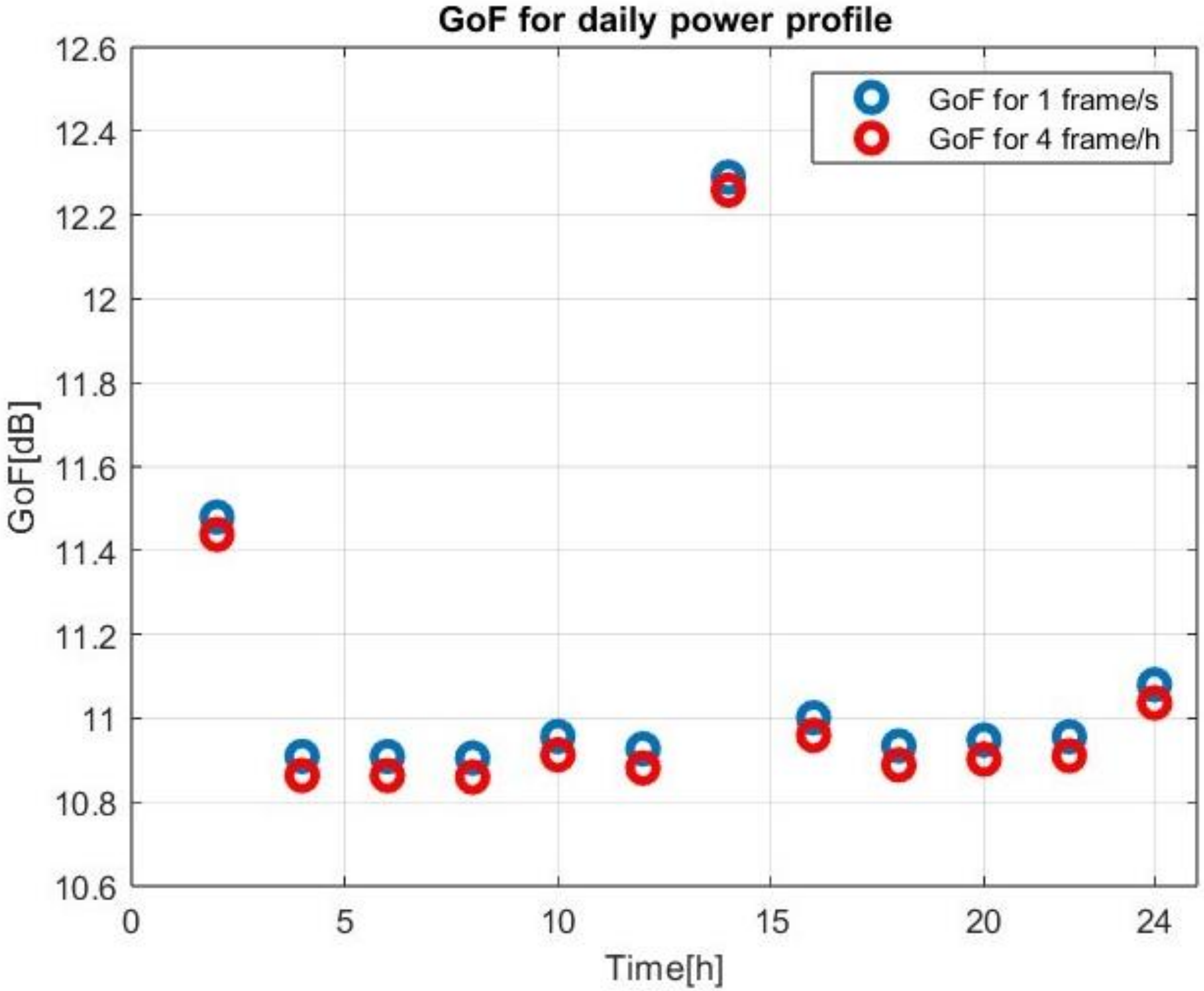
$$GoF = 20lg \frac{P_{max}}{\sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n}(P_i - P_{max})^2}}$$

GoF FOR POWER PROFILE VARIABILITY

Load power profile 01.03.2023



T_r = 2 h, T_a = 24 h



GoF FOR POWER PROFILE VARIABILITY

Daily *GoF* classified with one single value

$$GoF^{*} = 20lg\frac{P_{max}}{\left|\tilde{P}_j - P_{max}\right|}$$

$$\overline{P_j} = \frac{\sum_{i=1}^{n} P_{ij}}{n}, j = \overline{1,k}$$

$\tilde{P}_j$ is the daily average of the recorded load profile

T_r= 24 h, f_s = 1 frame/s, T_a = 31 days

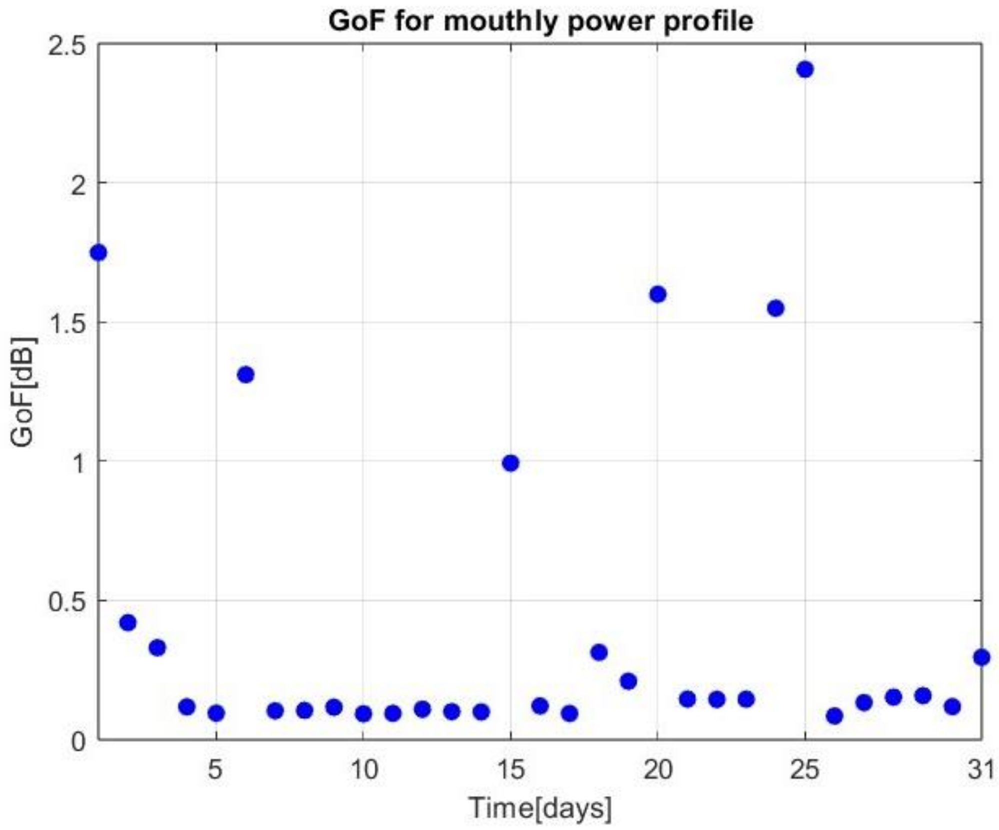
Monthly *GoF* classified with one single value

$$GoF^{**} = 20lg\frac{P_{max}}{\sqrt{\frac{1}{k-1}\sum_{j=1}^{k}\left(\overline{P_j} - P_{max}\right)^2}}$$

$$\overline{P_j} = \frac{\sum_{i=1}^{n} P_{ij}}{n}, j = \overline{1,k}$$

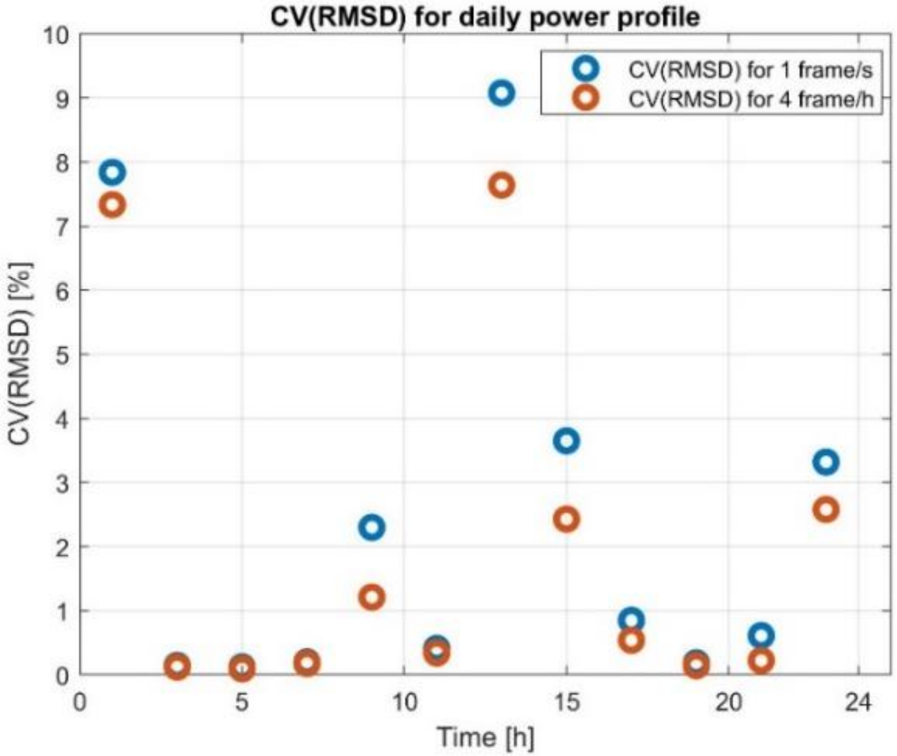
GoF^{**} = 0.25 dB

March 2023



CV(RMSD) FOR POWER PROFILE VARIABILITY

T_r = 2 h



T_r= 2 h, f_s = 1 frame/s, T_a = 24 h

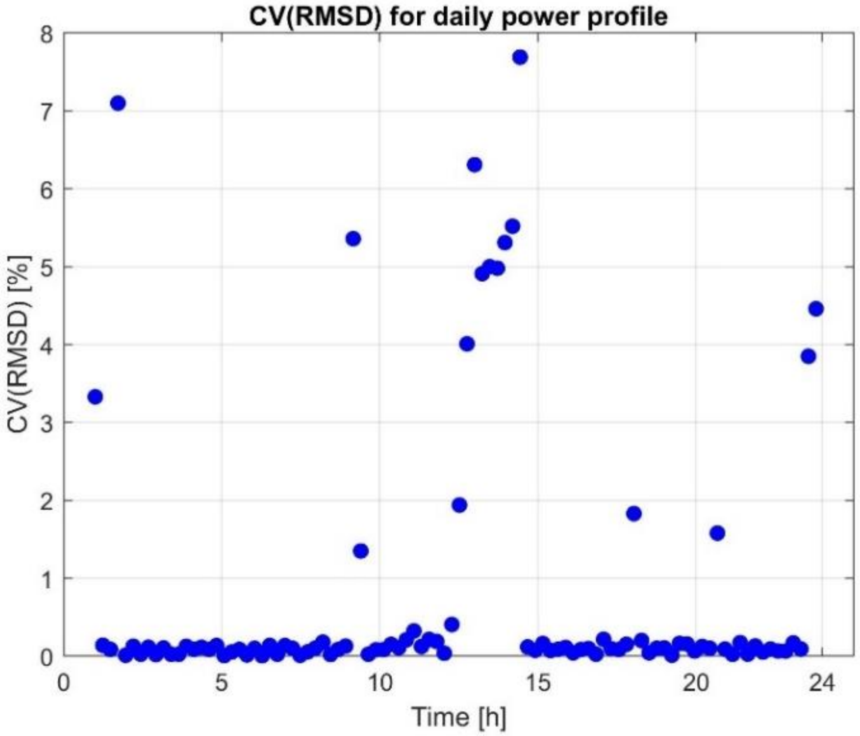
T_r= 2 h, f_s = 4 frames/h, T_a = 24 h

Day	CV(RMSD) [%]		
	min	median	max
1/3/2023	0.13	0.73	9.08
2/3/2023	0.18	1.76	8.15
3/3/2023	0.10	2.19	8.41
4/3/2023	0.15	1.07	7.64
5/3/2023	0.12	0.40	7.78
6/3/2023	0.04	0.39	7.39
7/3/2023	0.15	1.56	7.51
…	…	…	…
30/3/2023	0.14	3.44	8.50
31/3/2023	0.12	1.12	7.55

$$CV(RMSD) = \frac{1}{\bar{y}_p}\sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

CV(RMSD) FOR POWER PROFILE VARIABILITY

T_r = 15 minutes



$f_s = 1$ frame/s, T_a = 24 h

Day	CVRMSD [%]			
	min	median	P95	max
1/3/2023	0.01	0.11	5.32	7.69
2/3/2023	0.02	0.17	4.78	7.46
3/3/2023	0.00	0.11	5.54	8.19
…	…	…	…	…
17/3/2023	0.01	0.12	6.00	7.83
…	…	…	…	…
29/3/2023	0.01	0.14	4.93	9.68
30/3/2023	0.00	0.11	4.60	7.71
31/3/2023	0.01	0.11	5.74	7.57

CV(RMSD) FOR POWER PROFILE VARIABILITY

T_r = 2 h

Day	CV(RMSD) [%]		
	min	median	max
1/3/2023	0.13	0.73	9.08
2/3/2023	0.18	1.76	8.15
3/3/2023	0.10	2.19	8.41
4/3/2023	0.15	1.07	7.64
5/3/2023	0.12	0.40	7.78
6/3/2023	0.04	0.39	7.39
7/3/2023	0.15	1.56	7.51
…	…	…	…
30/3/2023	0.14	3.44	8.50
31/3/2023	0.12	1.12	7.55

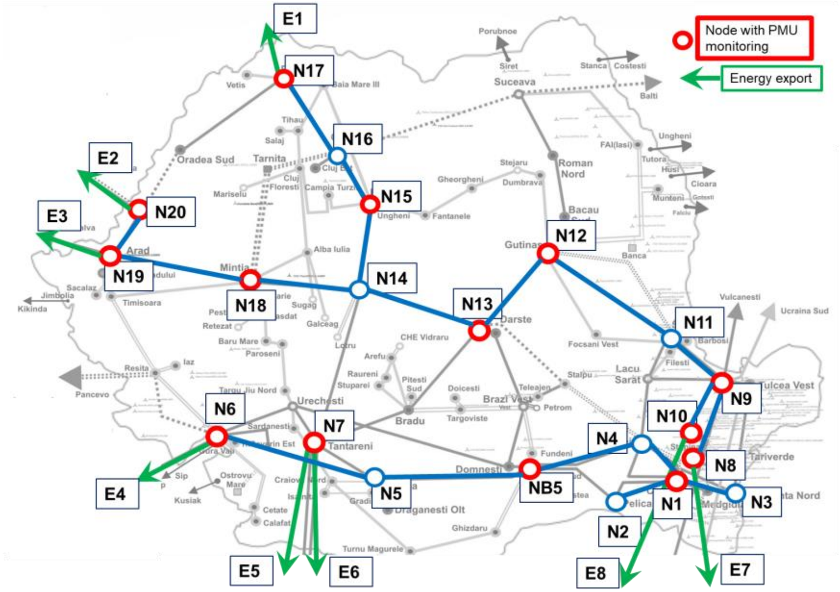
T_r = 15 minutes

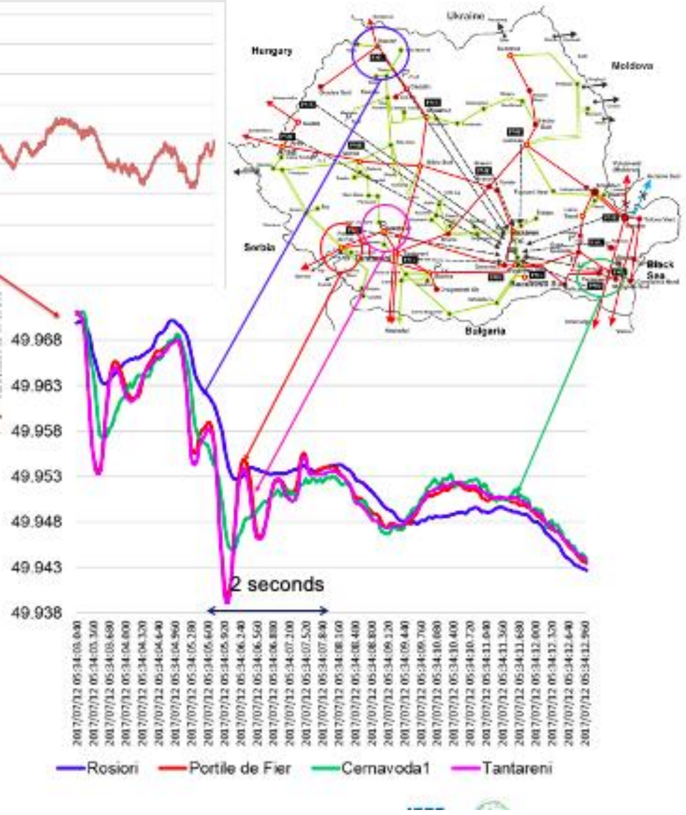
Day	CVRMSD [%]			
	min	median	P95	max
1/3/2023	0.01	0.11	5.32	7.69
2/3/2023	0.02	0.17	4.78	7.46
3/3/2023	0.00	0.11	5.54	8.19
…	…	…	…	…
17/3/2023	0.01	0.12	6.00	7.83
…	…	…	…	…
29/3/2023	0.01	0.14	4.93	9.68
30/3/2023	0.00	0.11	4.60	7.71
31/3/2023	0.01	0.11	5.74	7.57

f_s = 1 frame/s, T_a = 24 h

Example. Frequency Information in WAMCS using PMUs

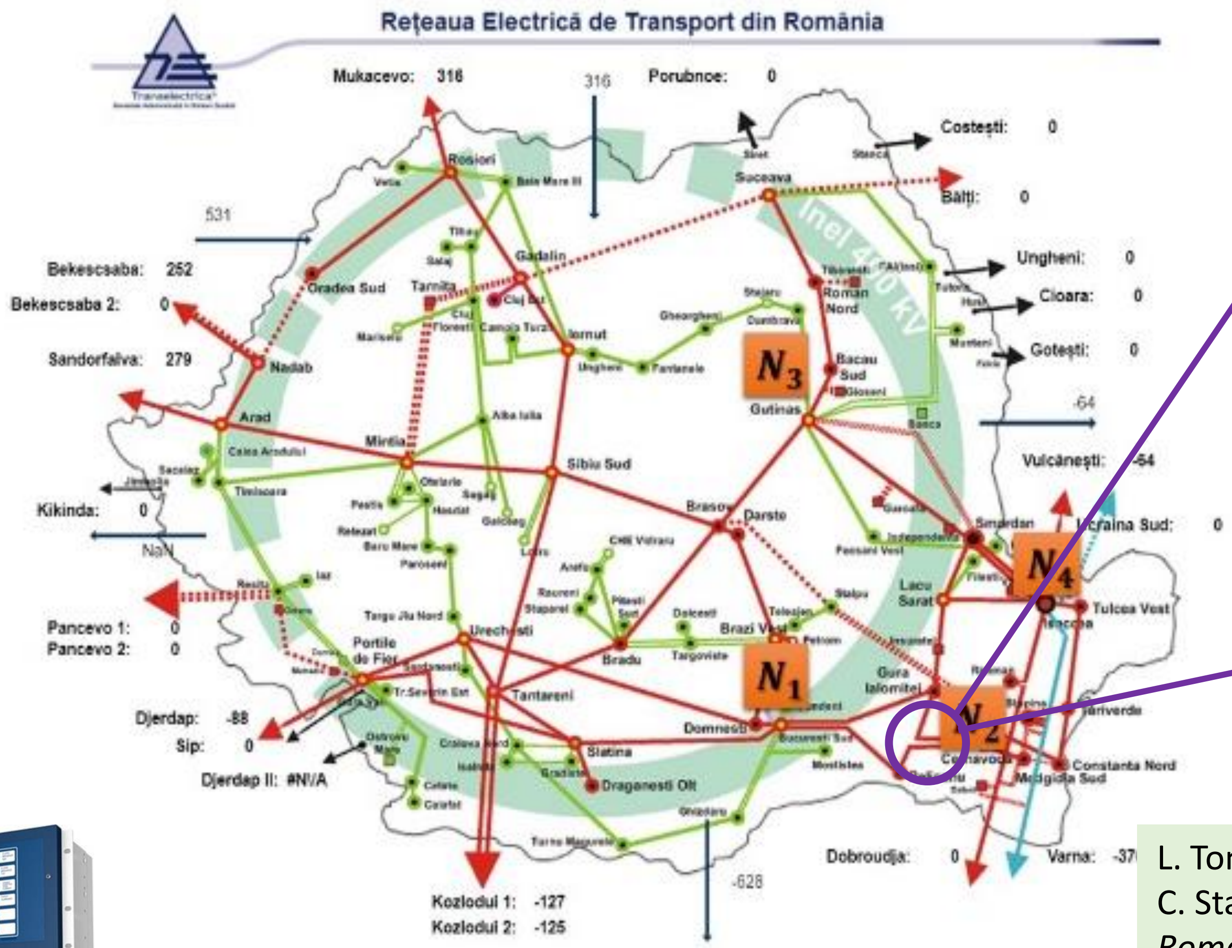
Analysis of frequency in case of generation loss caused by lightning





L. Toma et.ot., *Frequency analysis in the Romanian power system under large perturbations*, Proc. of 55th Universities Power Engineering Conference (UPEC 2020) – Torino, Italy, 1-4 September 2020

Examples of high reporting rates (PMUs). System inertia and frequency variability



Cernavoda Nuclear Power Plant 2 x 700 MW

CNPP_ev1: 1st June 2017

- One unit was under planned maintenance (half inertia available)
- Sudden full disconnection of the unit (no inertia remained)
- The instant of perturbation:
  - 18% wind generation
  - 17% power export

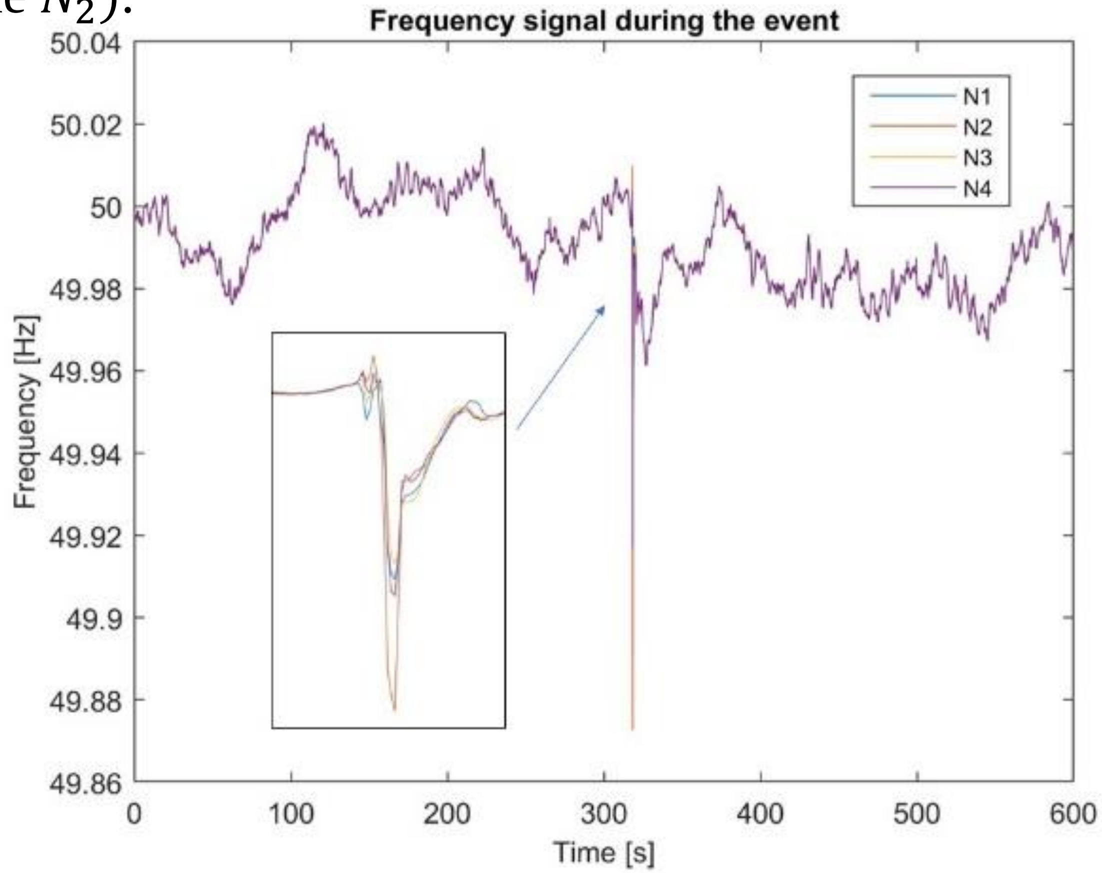
CNPP_ev2: 16 August 2018

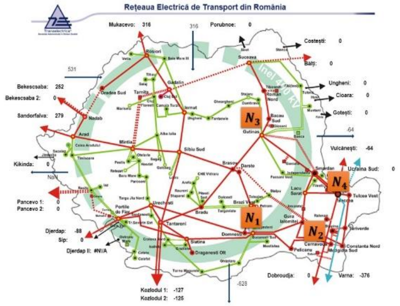
- Both units in operation
- Sudden full disconnection of the unit
- The instant of perturbation:
  - 4.4% wind generation
  - 6% power export

L. Toma, M. Sanduleac, M. Albu, C. Diaconu, C. Stanescu, *Frequency analysis in the Romanian power system under major grid disturbances*, CIGRE e-Session, 2020

METRICS FOR FREQUENCY VARIABILITY - WAMSC

Frequency variation during the **first event**, in 4 different nodes of the Romanian transmission system, for T_{ss} =10 minutes. Further we analysed the signal with the highest variability (node N_2).





A. P. Brîncoveanu, E. Fiorentis, A. -M. Dumitrescu and M. M. Albu, "Assessing Frequency Variability Using Long Term High Reporting Rate Measurements," 2023 Intern. Conf. on Electromechanical and Energy Systems (SIELMEN), Chisinau, Moldova, 2023, pp. 1-6

T_w= 1s

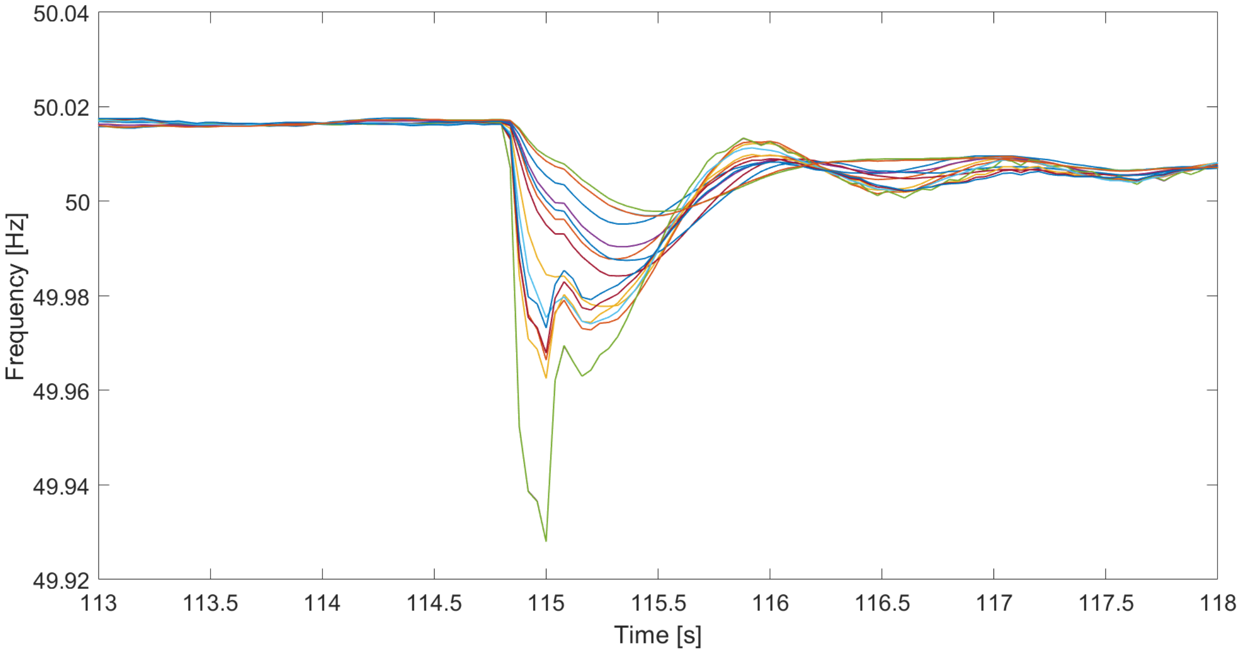
i	Metrics on $T_{w,i}$	
	CV(RMSE)	R^2
1	7.92E-06	0.9999
2	6.21E-06	1.0000
…	…	…
319	501E-04	0.9975
…	…	…
600	17.6E-06	0.9999

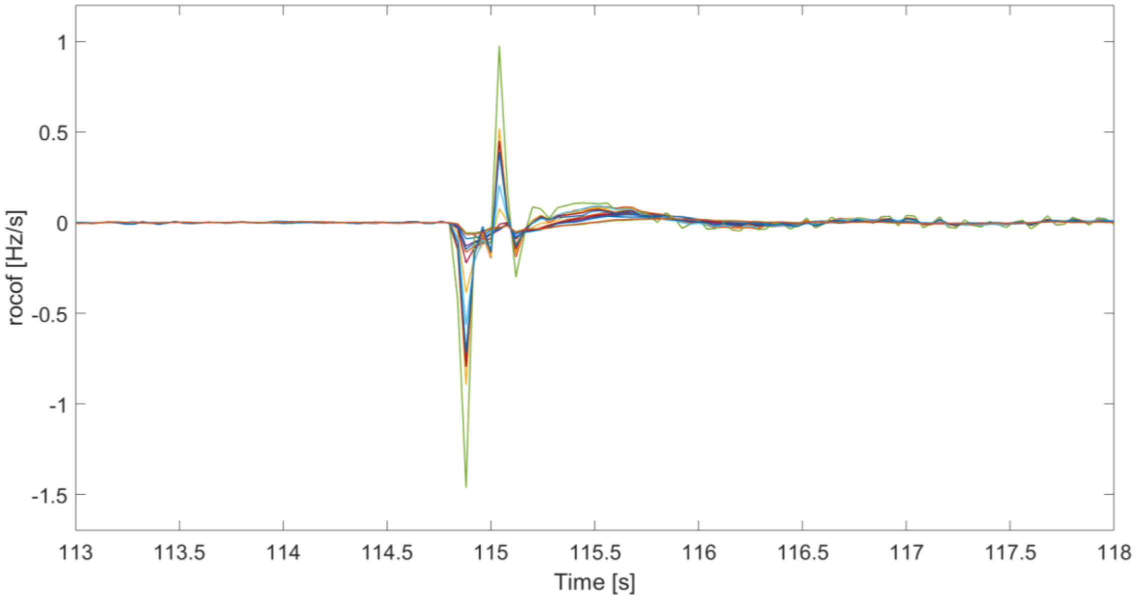
T_w= 200ms

i	Metrics on $T_{w,i}$	
	CV(RMSE)	R^2
1	3.71E-06	1.0000
2	1.96E-06	1.0000
…	…	…
1594	876E-06	0.9923
…	…	…
3000	1.60E-06	1.0000

METRICS FOR FREQUENCY VARIABILITY - WAMSC

Frequency variation during the second **event** for T_{ss} =10 minutes.





METRICS FOR FREQUENCY VARIABILITY - WAMSC

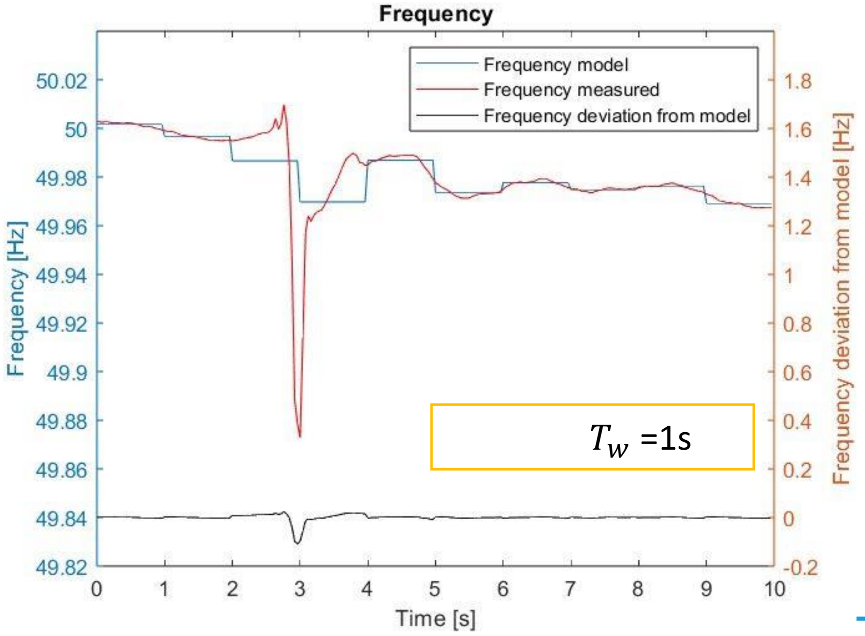
To better highlight the frequency variability: analyse the difference between the signal f_i and a selected signal (model) **for the case of pattern timeline of the T_w =1s**. The selected pattern f_{model} is described by:

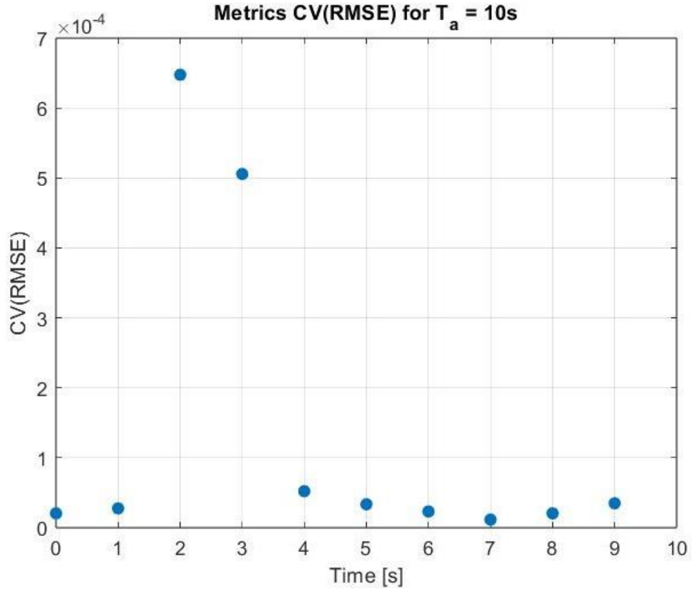
$$f_k^* = \frac{\sum_{N_w(k-1)+1}^{kN_w} f_i}{N_w}, k = \overline{1,10}$$

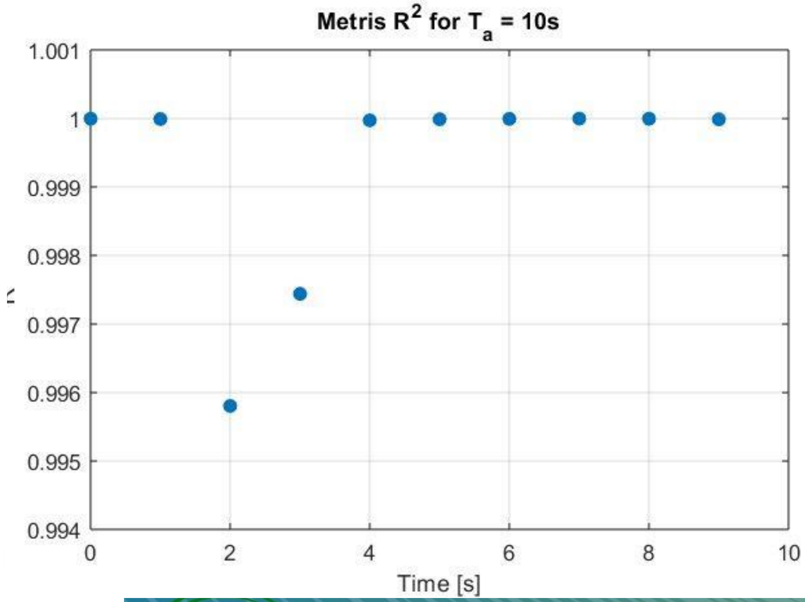
$$N_w = \frac{T_w}{T_{PMU}} = 25;$$

$$f_{model,i} = f_k^*, for\ N_w(k-1) + 1 < i < kN_w$$

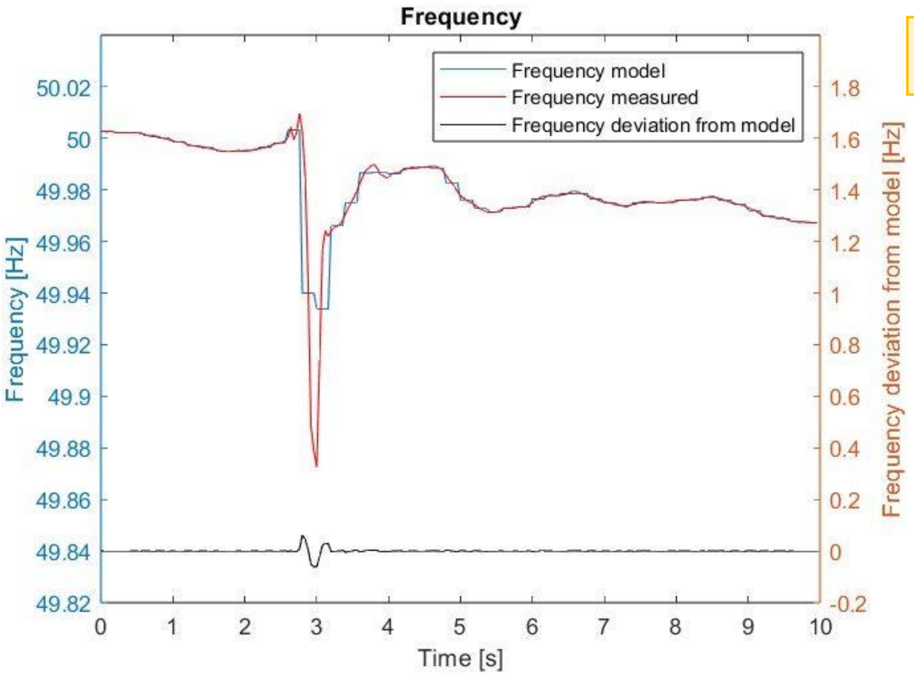
$$\Delta f_{model} = f_i - f_{model}$$







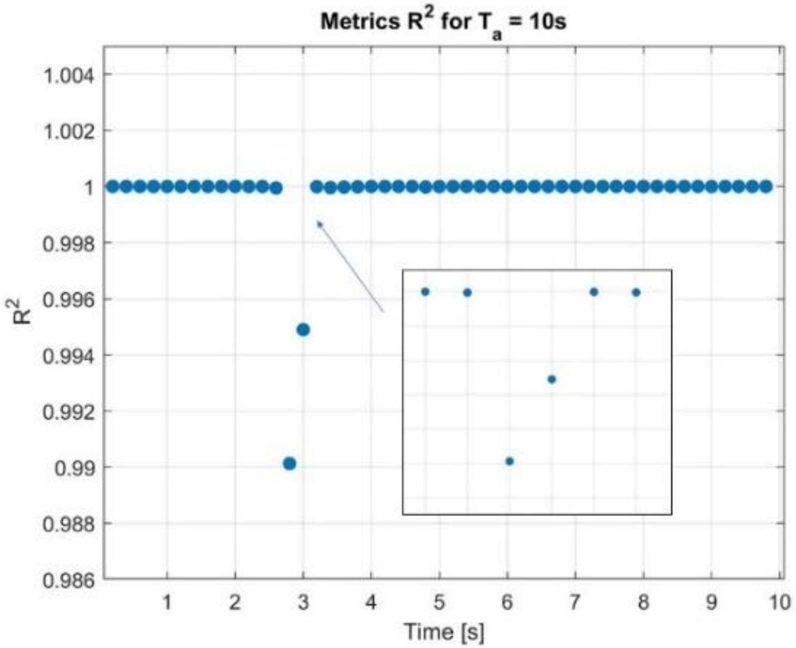
METRICS FOR FREQUENCY VARIABILITY - WAMSC

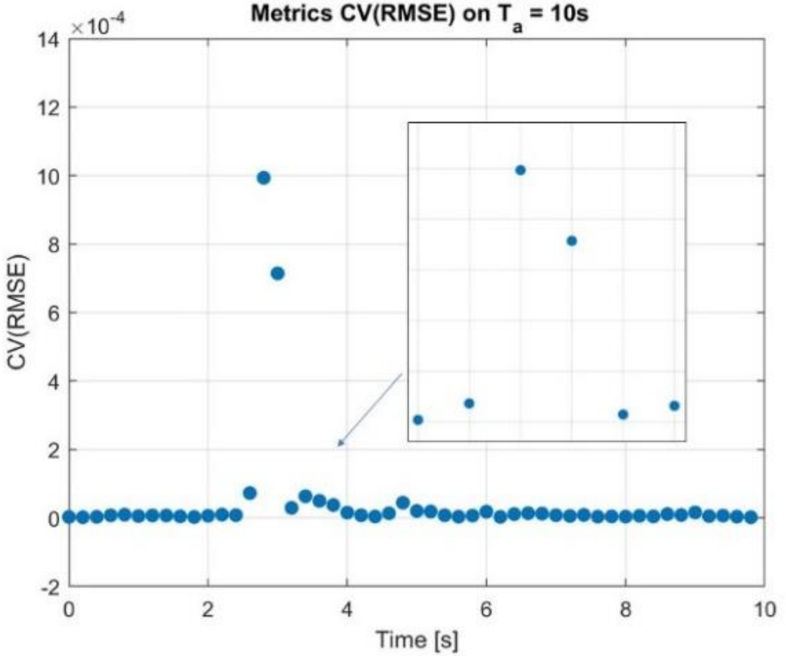


T_w =200 ms

$$N_w = \frac{T_w}{T_{PMU}} = 5;$$

$$f_k^* = \frac{\sum_{N_w(k-1)+1}^{kN_w} f_i}{N_w}, k = \overline{1,50}$$

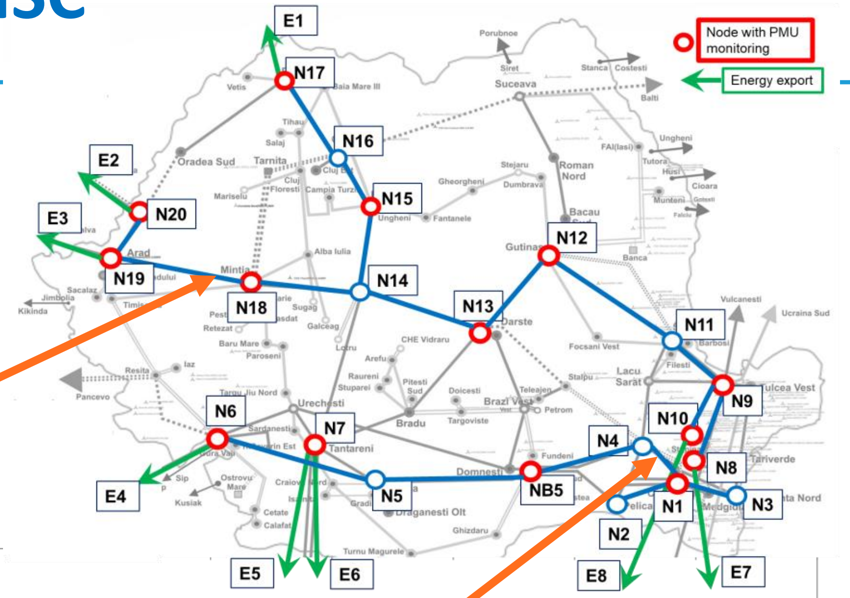


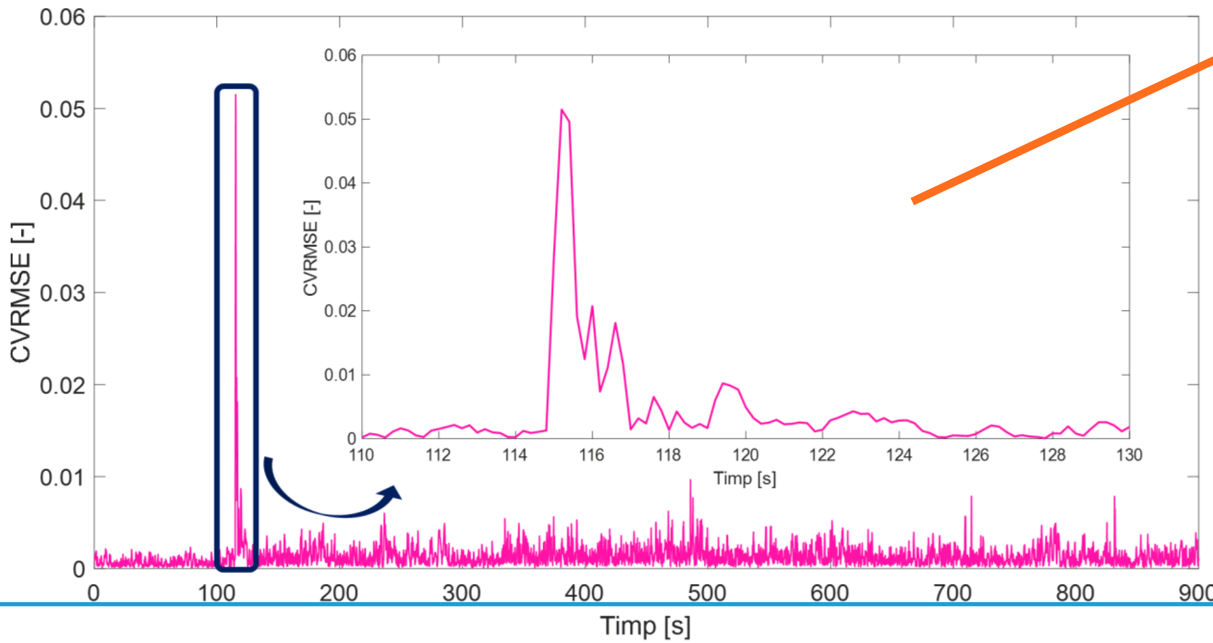


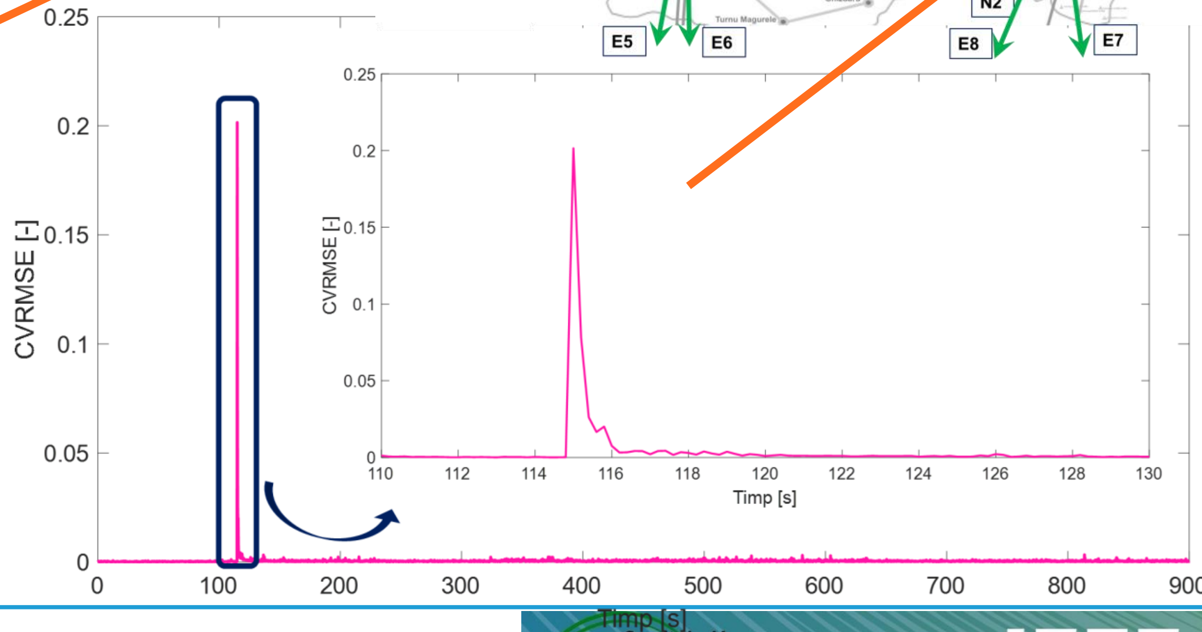
A. P. Brîncoveanu, E. Fiorentis, A. -M. Dumitrescu and M. M. Albu, "Assessing Frequency Variability Using Long Term High Reporting Rate Measurements," 2023 Intern. Conf. on Electromechanical and Energy Systems (SIELMEN), Chisinau, Moldova, 2023, pp. 1-6,

METRICS FOR POWER FLOW VARIABILITY - WAMSC

$$CV(RMSE) = \frac{1}{\bar{y}}\sqrt{\frac{\sum_{i=1}^{N_w}(x_i - y_i)^2}{N_w}}$$

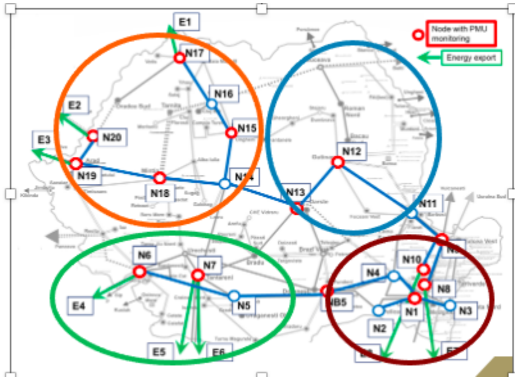


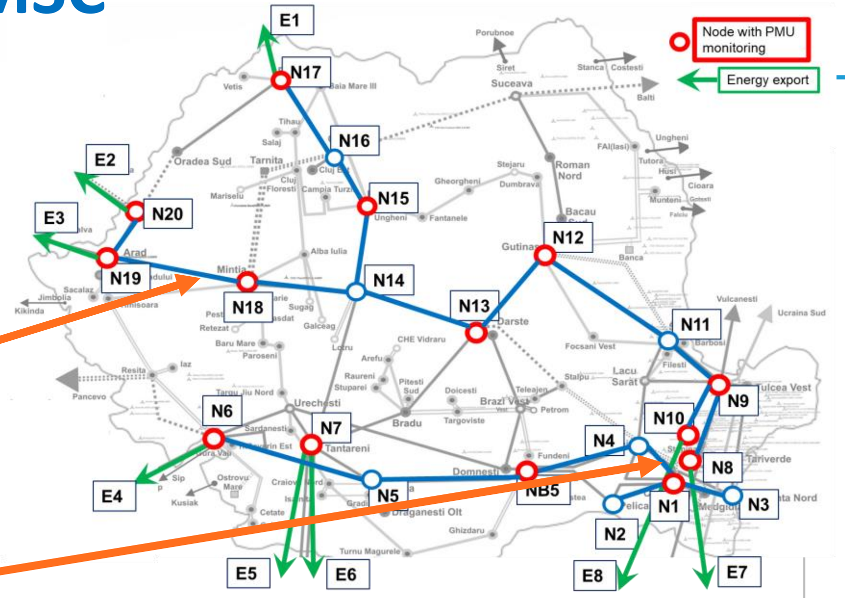


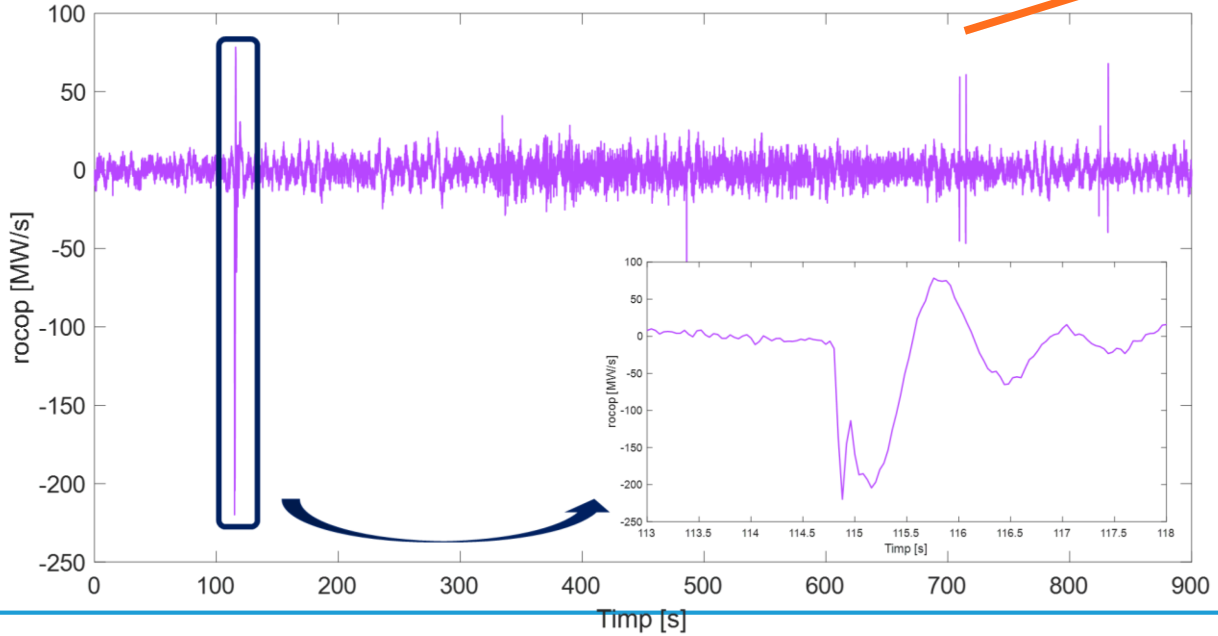


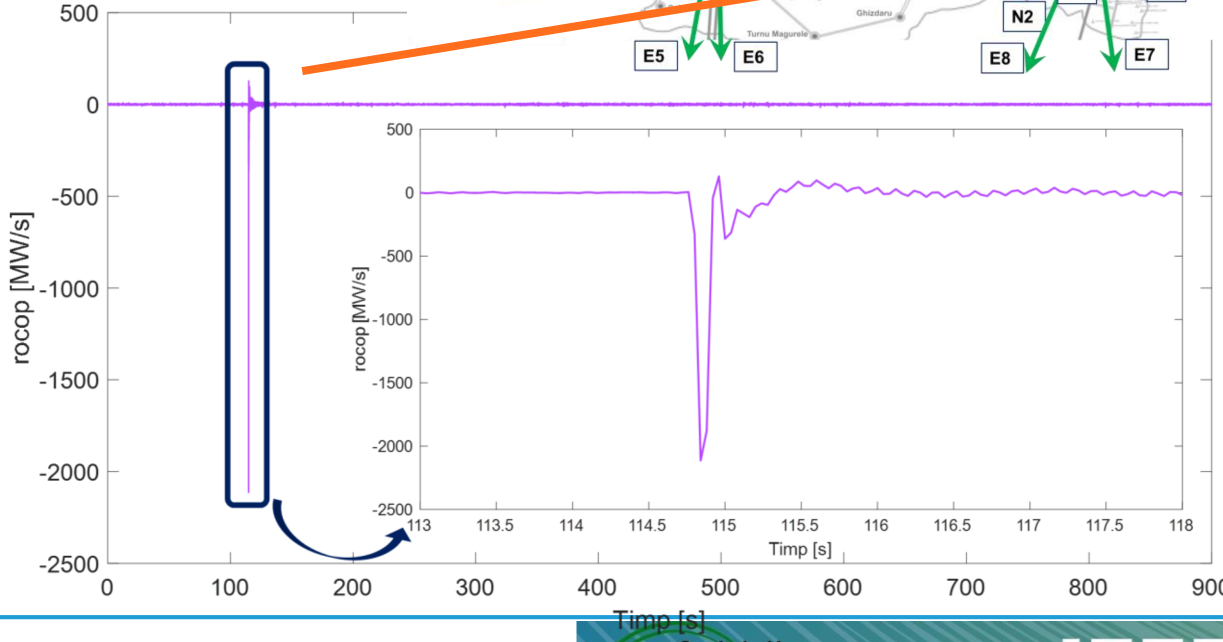
METRICS FOR POWER FLOW VARIABILITY - WAMSC

$$rocop(t_j) = \frac{P(t_{j+1}) - P(t_j)}{T_r}$$





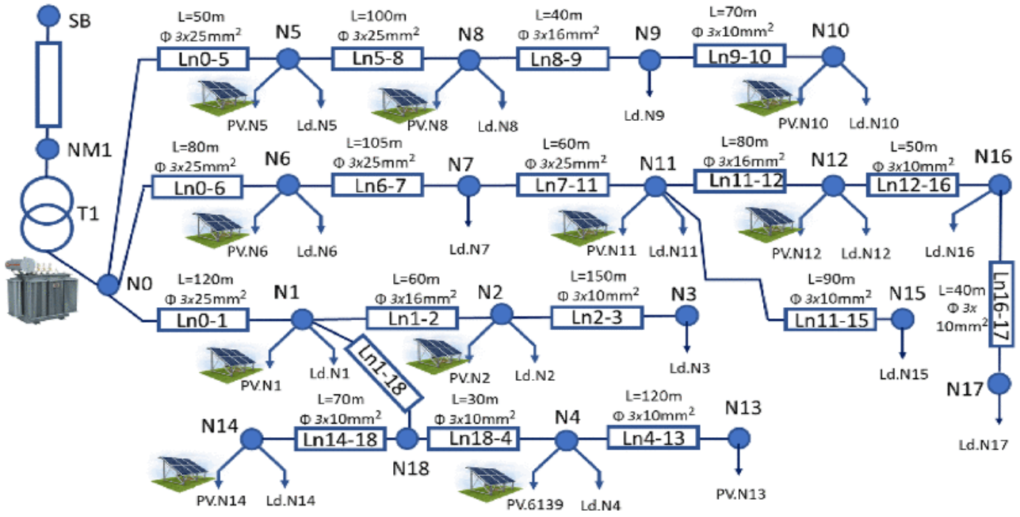


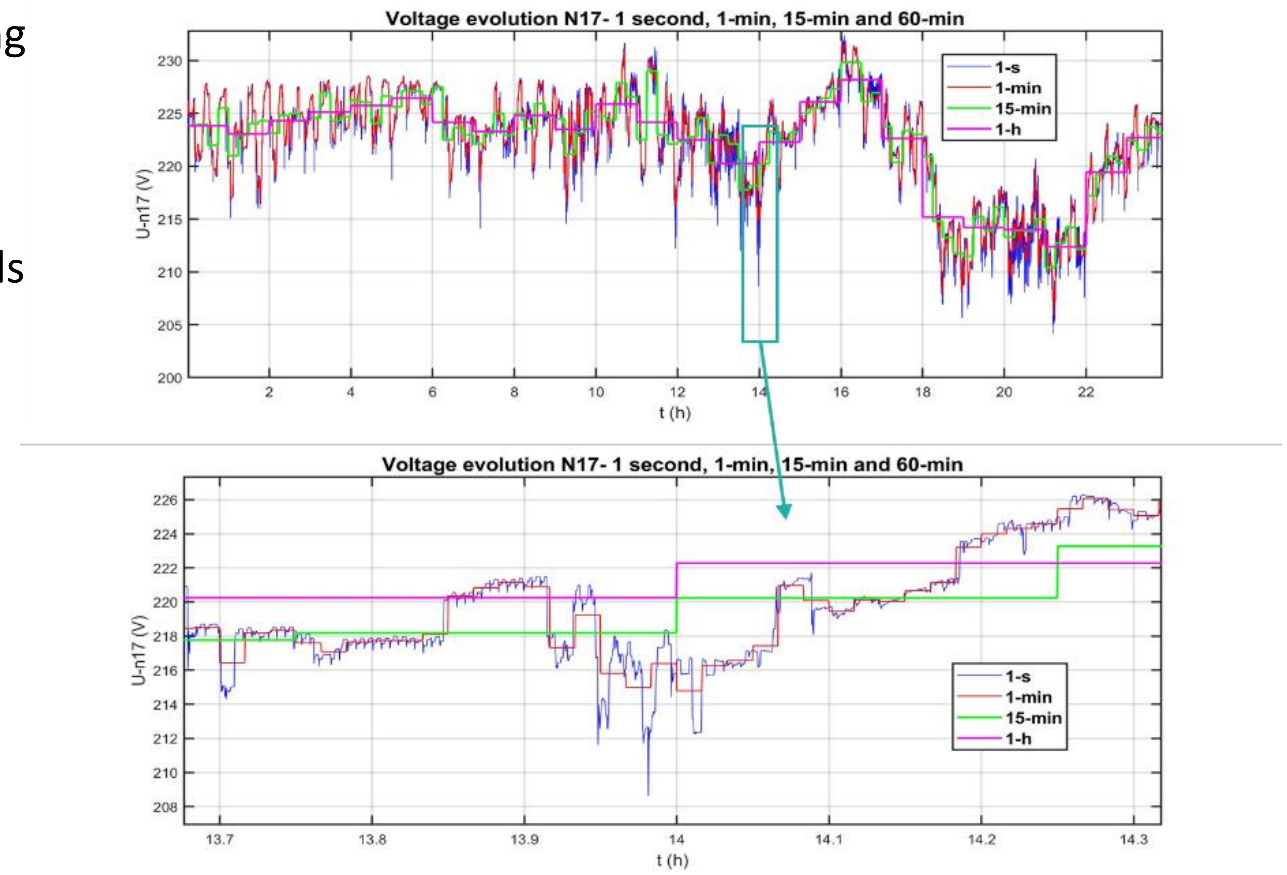


POWER PROFILES AND ENERGY COMMUNITIES.
[ANOTHER] EXAMPLE OF DATA ANALYTICS

→ fusion of data recorded at significantly different reporting rates → increase the situational awareness

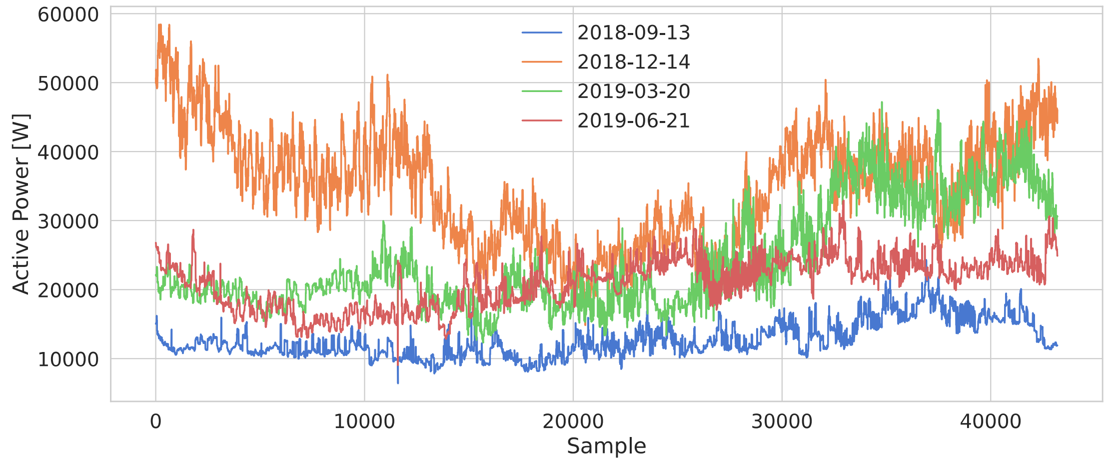
→framework for knowledge extraction from HRR data. The process takes place at smart meter level → to increase the accuracy of the monitoring tools for distribution power grids **by using statistics (**the percentiles - e.g., p95 and p99 and the cdf) **able to capture system dynamics relevant for network diagnosis**.





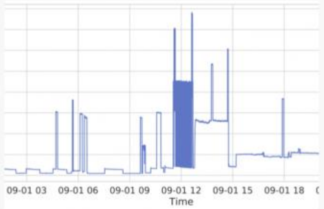
M. Sanduleac, V. I. Ciornei, L. Toma, R. Plamanescu, A. -M. Dumitrescu and M. Albu, "High reporting rate smart metering data for enhanced grid monitoring and services for energy communities," in *IEEE Transactions on Industrial Informatics*, 2021

Datasets. Dissimilarity vs. Variability



RESIDENTIAL SMART METER ENERGY TIME SERIES: ACTIVE POWER MEASUREMENTS WITH 1S REPORTING RATE

View | Edit



Citation Author(s): Grigore Stamatescu (University Politehnica of Bucharest)
Mihaela Albu (University Politehnica of Bucharest)
Mihai Sanduleac (University Politehnica of Bucharest)

Submitted by: Grigore Stamatescu

Last updated: Wed, 09/28/2022 - 04:02

DOI: 10.21227/3yea-xm39

Data Format: *.txt; *.zip

Link to Paper: The unbundled smart meter concept in a synchro-SCADA framework

Links: Multiscale Data Analytics for Residential Active Power Measurements through Time Series Data Mining

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452 Views

Categories: Power and Energy, Computational Intelligence

Keywords: energy time series, smart meter, active power, data analytics

0 ratings - click the stars to submit your rating

ACCESS DATASET | CITE | SHARE/EMBED

STUDENT BUILDING SMART METER ENERGY TIME SERIES: ACTIVE POWER MEASUREMENTS WITH 2S TIME RESOLUTION FOR 1 YEAR

1 rating - Please login to submit your rating.

Citation Author(s): Andrei Ionică
Radu Plămănescu
Mihaela Albu
Mihai Sănduleac

Submitted by: Andrei Ionica

Last updated: Fri, 06/30/2023 - 05:27

DOI: 10.21227/ywtf-x329

Data Format: *.avi; *.csv; *.txt; *.zip

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180 Views

Categories: Power and Energy

Keywords: household appliances; power profiles; active power; reactive power

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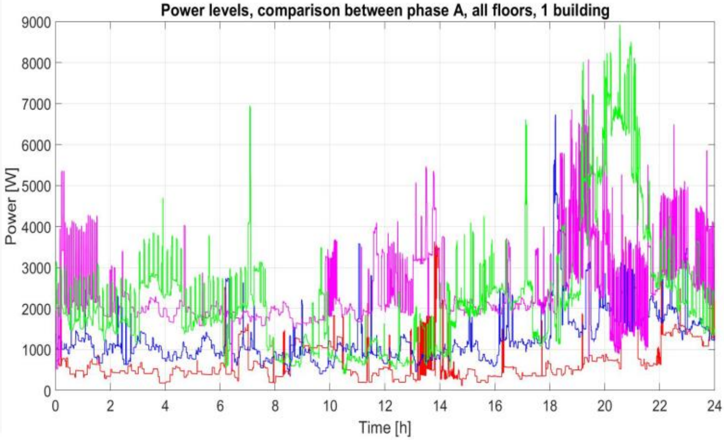
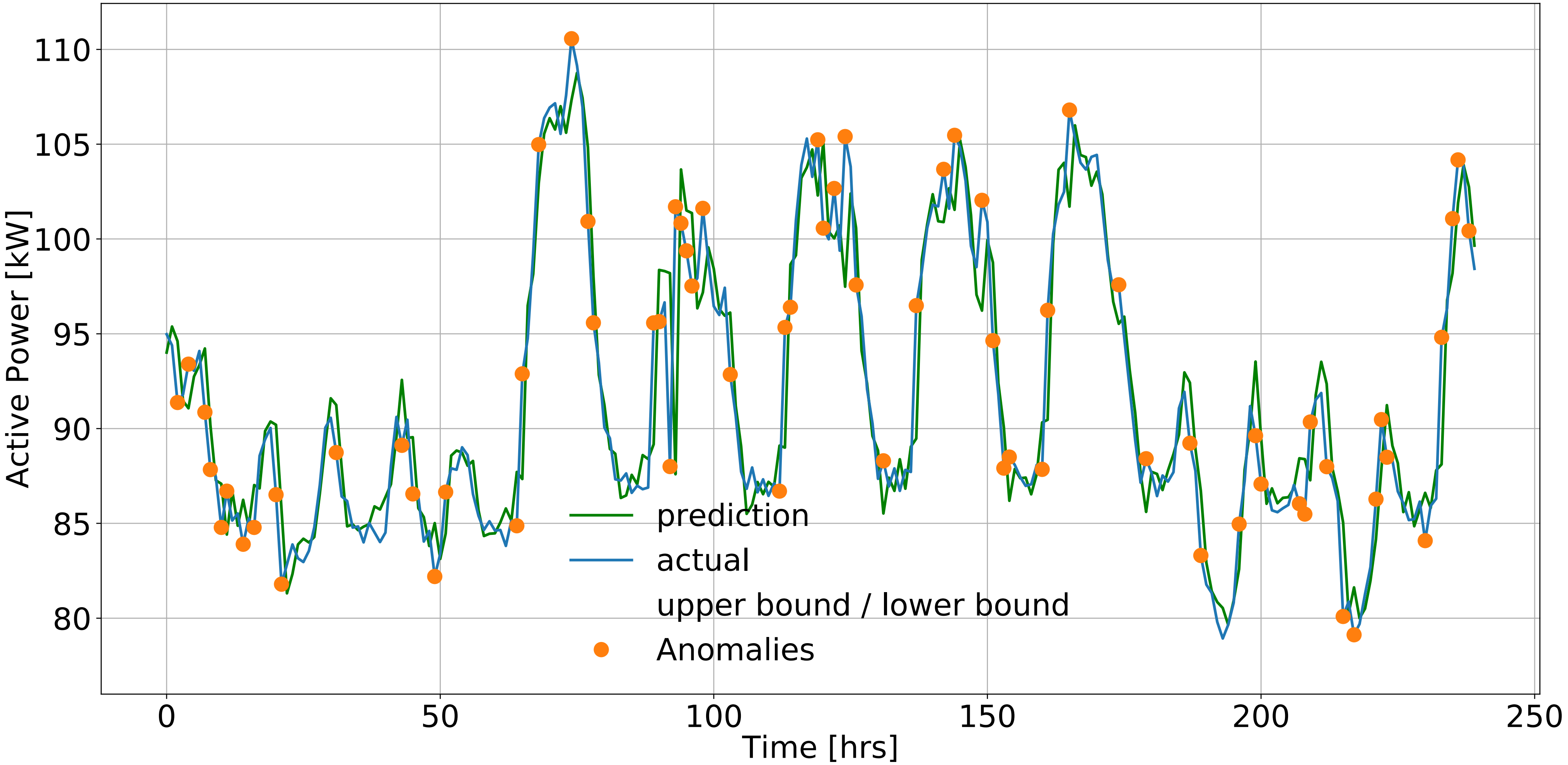
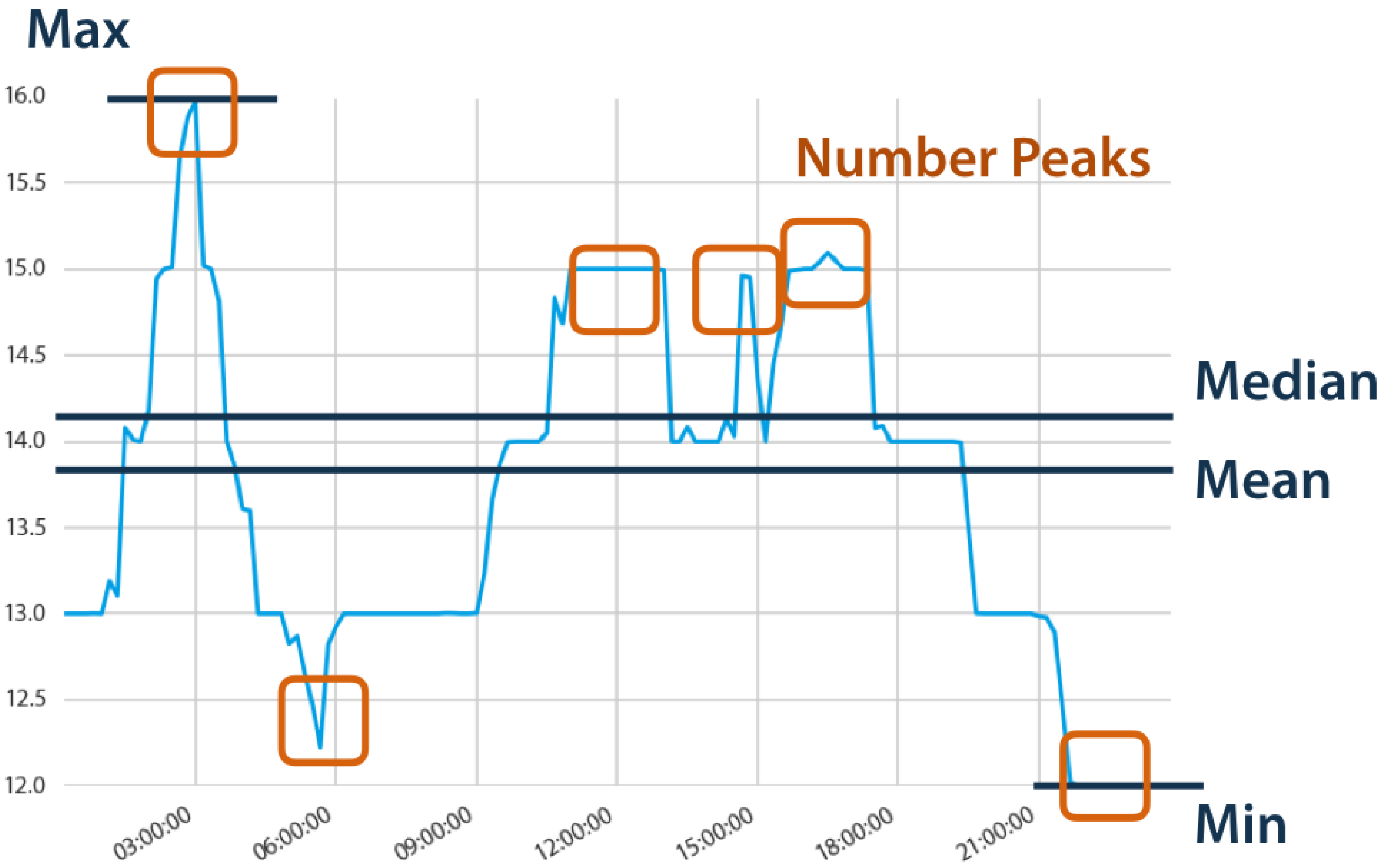


Application: Energy forecasting in buildings



Automatic Feature Extraction – *tsfresh*



Christ, M., Braun, N., Neuffer, J., & Kempa-Liehr, A. W. (2018). *Time series feature extraction on basis of scalable hypothesis tests (tsfresh– a python package)*. Neurocomputing, 307, 72-77.

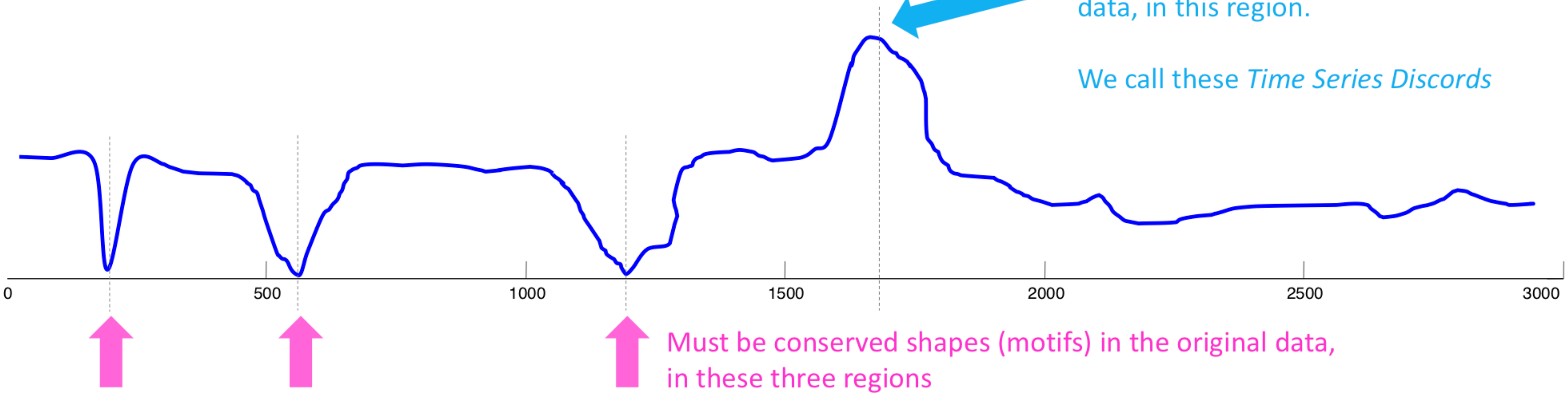
Matrix Profile (MP) Technique

- Data structure and family of algorithms for the efficient description of time series
- The matrix profile at location *i* records the (normalised Euclidean) distance of the subsequence *T* in position *i* to its nearest neighbor

C. M. Yeh et al., *"Matrix Profile I: All Pairs Similarity Joins for Time Series: A Unifying View That Includes Motifs, Discords and Shapelets,"* 2016 IEEE 16th International Conference on Data Mining (ICDM), Barcelona, 2016

Must be an anomaly in the original data, in this region.

We call these *Time Series Discords*



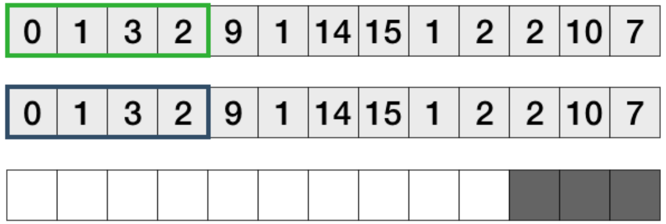
Must be conserved shapes (motifs) in the original data, in these three regions

Forecasting. Multi-Scale Data Analytics for Power Profiles. Matrix profile

MP is computed as a vector of values containing the minimum z-normalised Euclidean distance d, by sliding a window of size m over a time series T of size n:

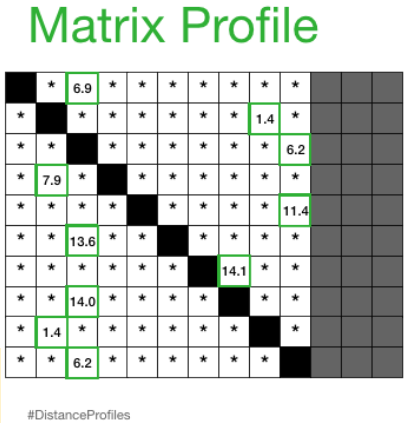
$$d\left(T_a, T_b\right) = \sqrt{\sum_{i=1}^{n} \left(T_{a,i} - T_{b,i}\right)^2}$$

Various computationally efficient libraries and algorithms available



MP was investigated for the following features:

- **Load and generation power profiles**
- Added noise over input information
- Anomaly (discords) detection
- Evaluating the robustness of the MP

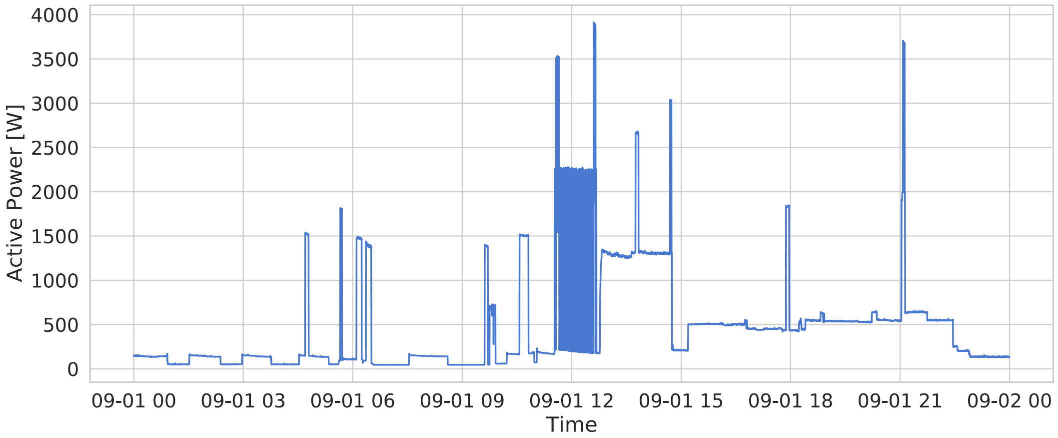


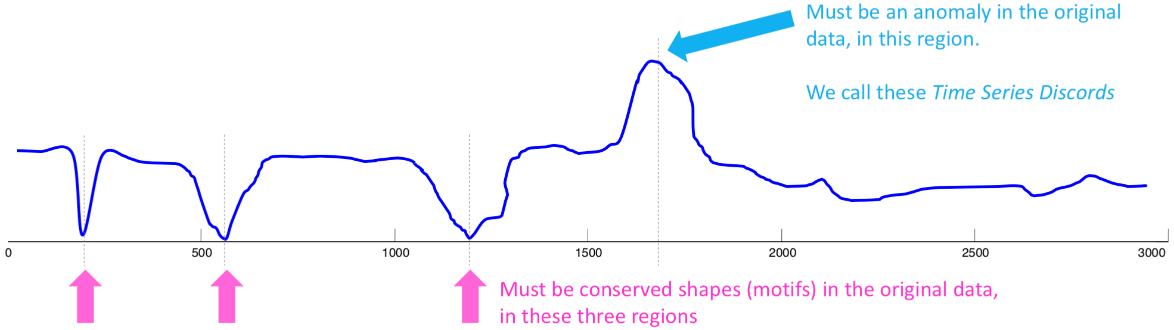
https://stumpy.readthedocs.io/en/latest/Tutorial_The_Matrix_Profile.html

MULTI-SCALE DATA ANALYTICS FOR POWER PROFILES

- Development of **data driven models** that operate in a robust manner at various timescales
- Incorporate domain knowledge at pre-processing and feature engineering stages
- Potential for model compression to run on embedded hardware with resource constraints
- **Micro-load forecasting and classification e.g. steady state and transients labelling**
- **How do data-driven models perform under varying input reporting rates? Can we keep the same models w/o retraining?**
- One month of residental energy measurements sampled at 1s; Offline processing of daily text record files

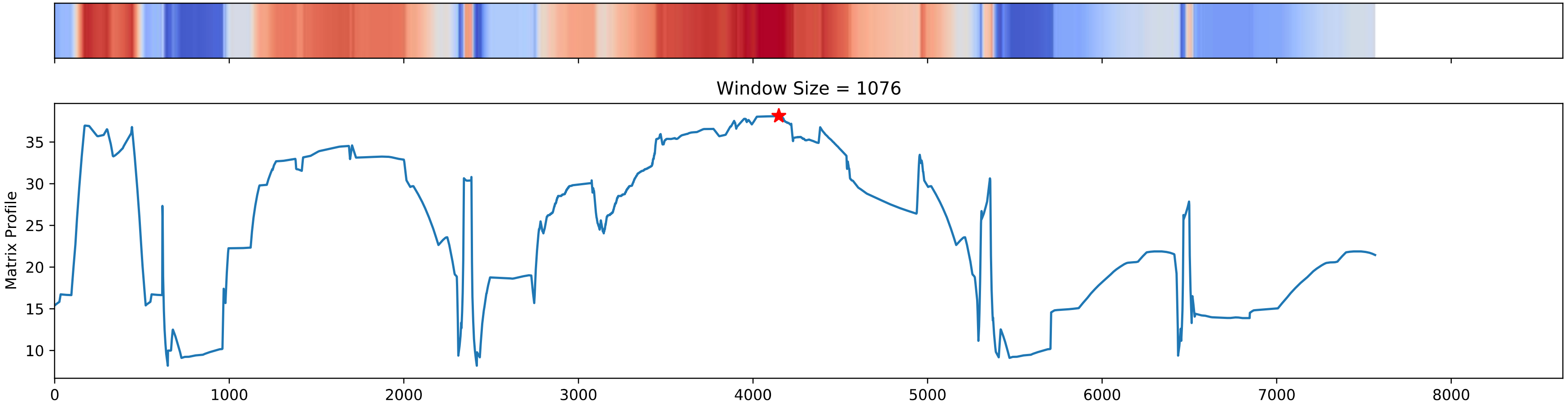
Grigore Stamatescu, Irina Ciornei, Radu Plamanescu, Ana-Maria Dumitrescu, Mihaela Albu, *Reporting Interval Impact on Deep Residential Energy Measurement Prediction*, Proc. of AMPS2021, 1 Oct. 2021



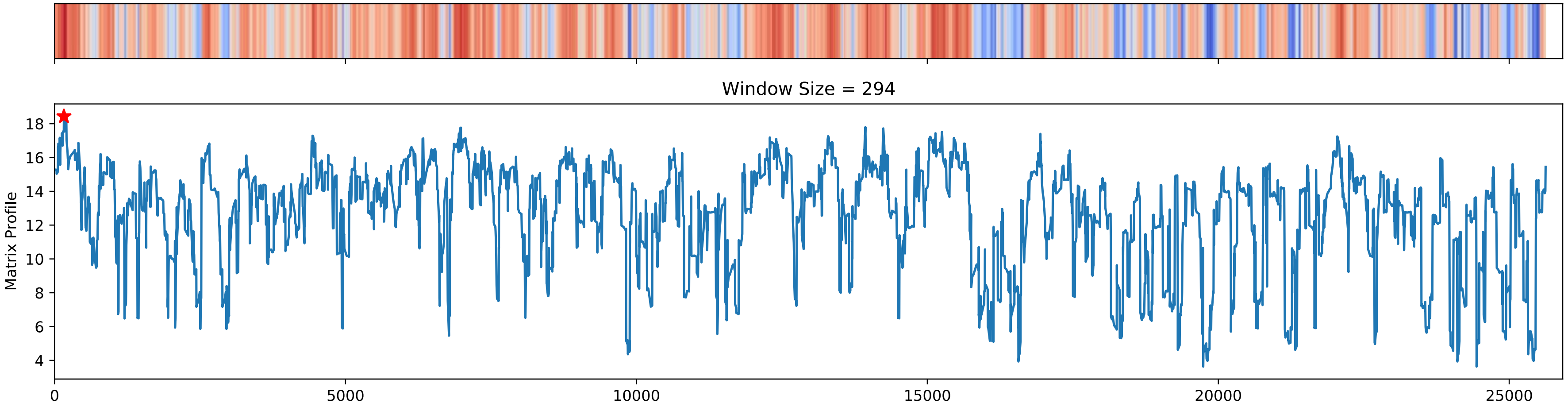


Multi-Scale Data Analytics for Power Profiles. Dissimilarity vs. Variability

Matrix Profile to identify most dissimilar sequence in **the daily data (noon)**



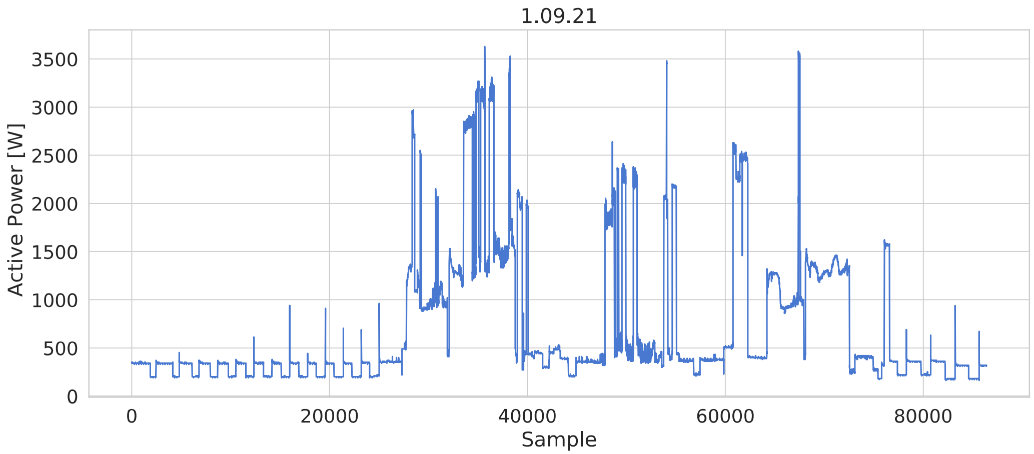
Matrix Profile to identify most dissimilar sequence in **the monthly data (Sept. 1st)**



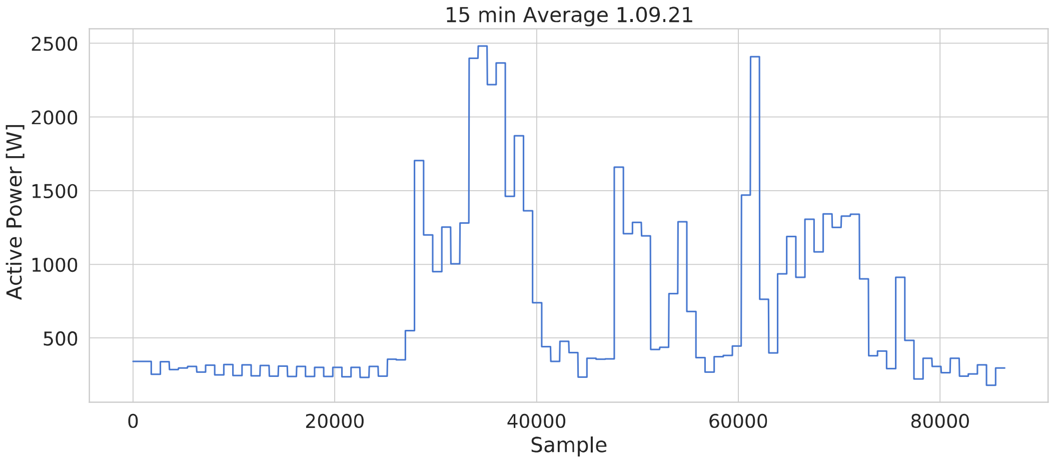
Grigore Stamatescu, et ot., *Reporting Interval Impact on Deep Residential Energy Measurement Prediction*, Proc. of AMPS2021, 2021

DATA SETS

- Daily power profile from measurements with 1 frame/s reporting rate – Example

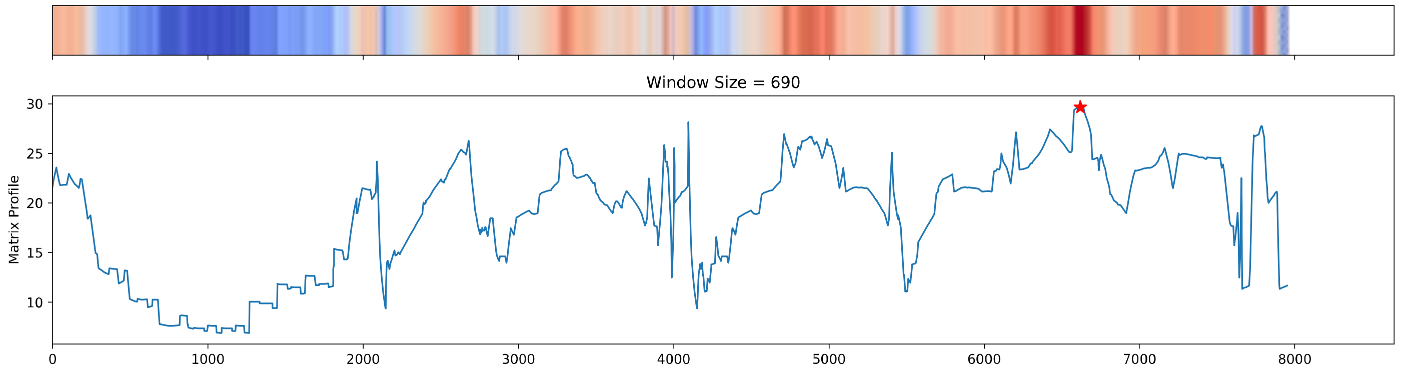


- Daily power profile from emulated meters with 4 frames/h reporting rate, using linear averaging

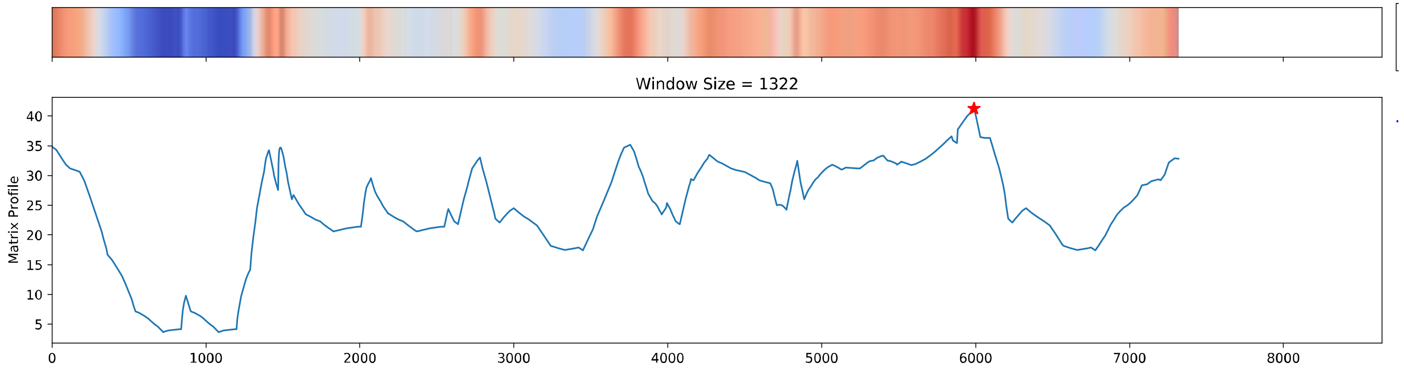


Daily Matrix Profiles

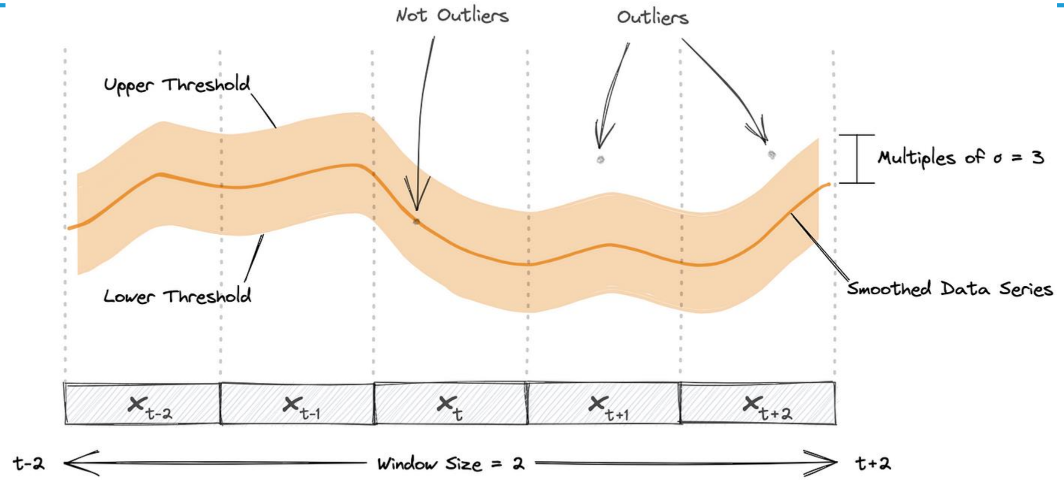
- Daily matrix profile: 1 frame/s reporting rate input measurements



- Daily matrix profile: averaged data



Anomaly Detection – Hampel Filter



- Uses a sliding window applied to the measurement time series in which the individual values are compared to the statistical distribution of their neighbours to flag and replace the considered outliers in the original time series
- Median Absolute Deviation (MAD) indicator represents the median of the absolute deviations from the median

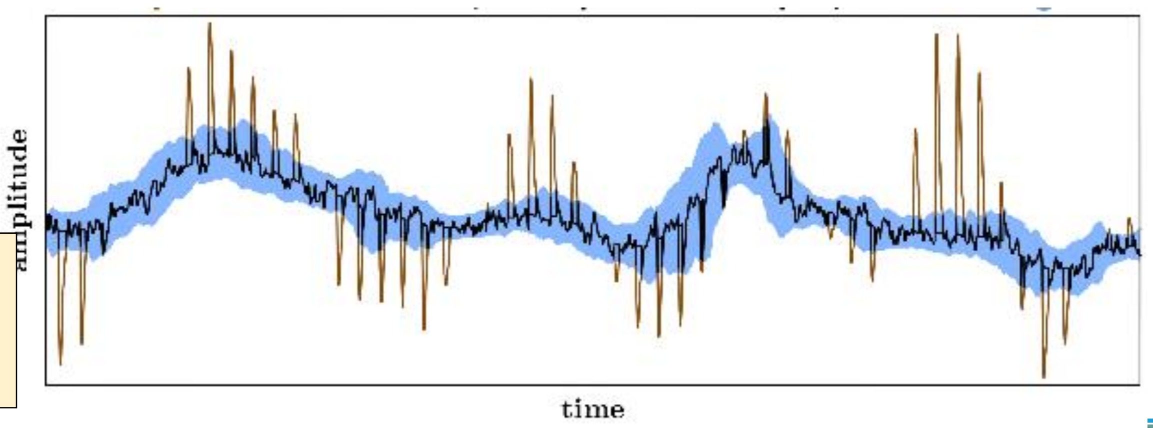
$$MAD = median(|X_i - \tilde{X}|)$$

- MAD linked to SD through:
  - k – scale factor (~1.486 for Normal distribution)

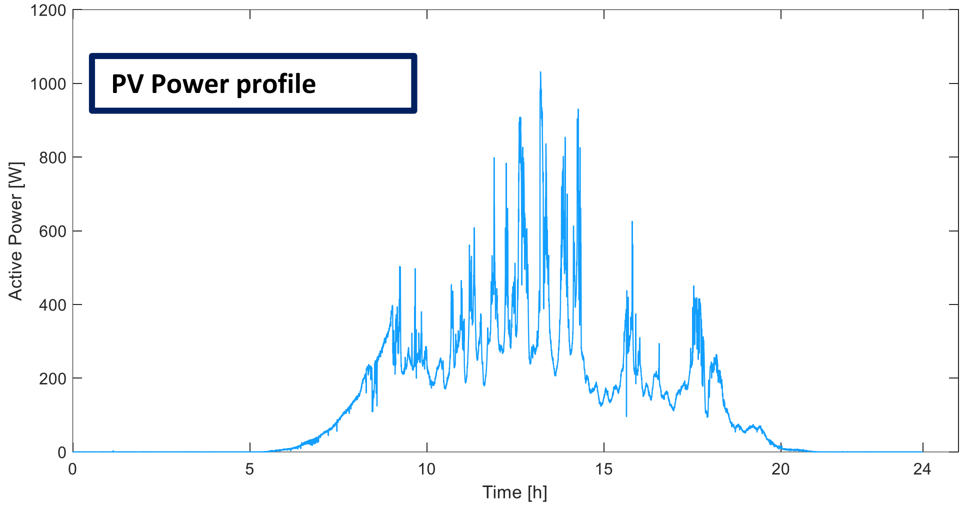
$$\hat{\sigma} = k \cdot MAD$$

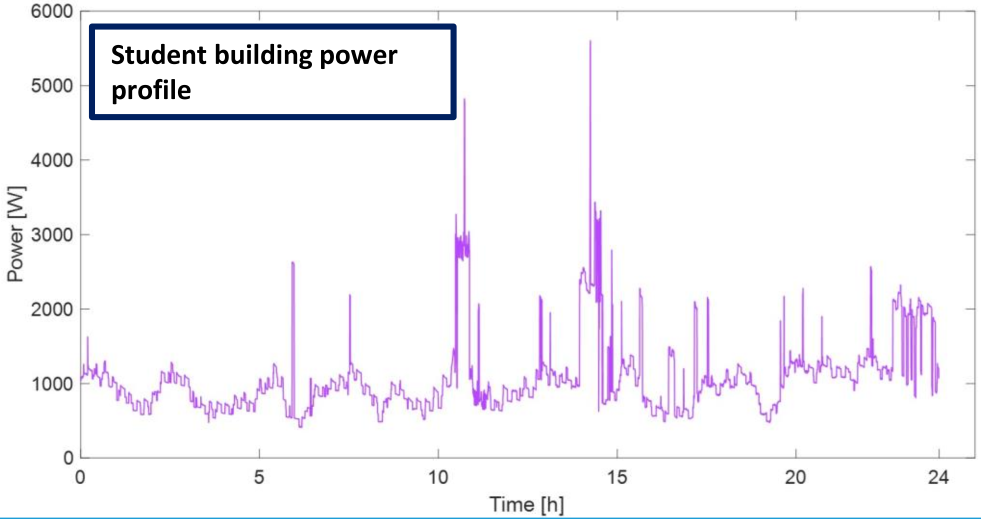
filtering yields an improvement in the prediction performance given **increased robustness** and lower variability of the input data

Grigore Stamatescu, et ot., *Leveraging Anomaly Detection and AutoML for Modelling Residential Measurement Power Traces,* Proc. of AMPS2023, 2023

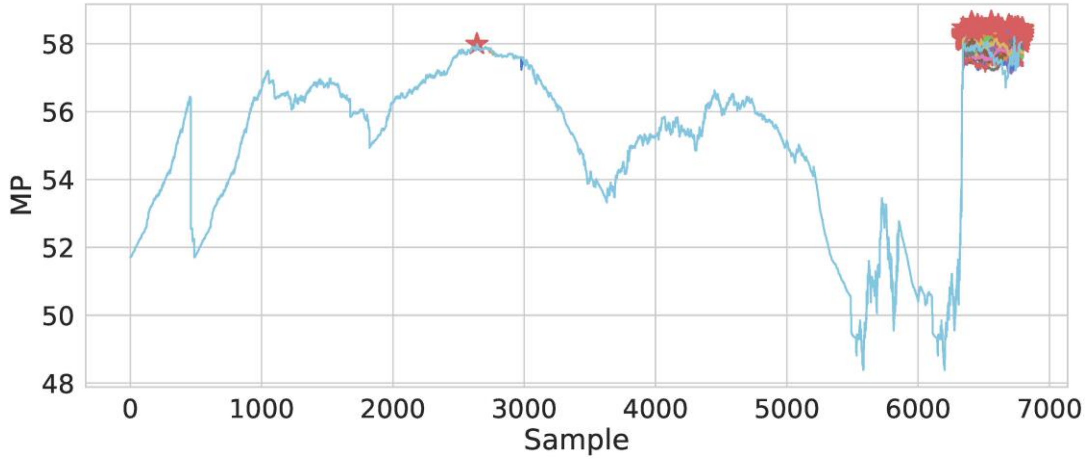


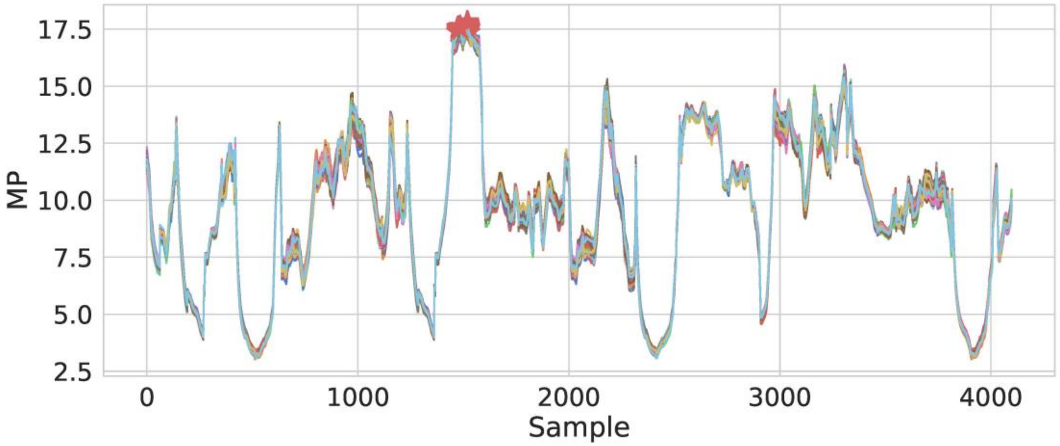
Multi-Scale Data Analytics for Power Profiles. Dissimilarity vs. Variability





Stability and robustness of the method: for varying noise level





WRAP-UP

- SMART[ER] POWER SYSTEMS: NEW PARADIGM FOR CONTROL
- MEASUREMENTS ARE LINKED TO INHERITED MODELS
- IMPORTANCE OF MEASUREMENT TIME, HIDDEN AGGREGATION AND REPORTING RATE
- HIGH REPORTING RATE MEASUREMENTS [SMART METERS]
- MEASURES OF VARIABILITY – INFORMATION LOSS, R^2, CV(RMSE), GOF
- EXAMPLE: VARIABILITY OF POWER PROFILES , VARIABILITY OF FREQUENCY E
- LEMENTS OF **DATA ANALYTICS** FOR LOW INERTIA ENERGY SYSTEMS
- FORECASTING BASED ON **OUTLIERS FILTERING** (AS A FUNCTION OF VARIABILITY)

Q&A session

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